

ABSTRACT

Title of thesis: ALL ABOUT CONGESTION: MODELING
DEPARTURE TIME DYNAMICS AND ITS
INTEGRATION WITH TRAFFIC MODELS

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This thesis comprehensively studies departure time choice models, and analyzes the consequent system-level peak spreading effects. In modeling, the school of discrete choice models successfully reveals the user heterogeneity. A mixture logit model and a latent class model based on the notion of carpooling preference have been estimated. Then a novel positive approach has been developed, which avoids the assumptions of rationality and focuses on how individuals actually make departure time decisions. Following this positive theory, we specify Bayesian learning, empirically estimate search start and stopping conditions that vary among users, and empirically derive search and decision rules from a joint reveal/stated-preference survey dataset. This innovative behavioral model is integrated with a traffic simulation model for a real-world study. Findings from this application reveal the potential of the proposed model to capture network dynamics and behavioral reactions. This integrated framework also provides a valuable tool for the evaluation of new transportation infrastructures, policies, and operation strategies.

ALL ABOUT CONGESTION: MODELING DEPARTURE TIME
DYNAMICS AND ITS INTEGRATION WITH TRAFFIC
MODELS

by

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Dedication

To my beloved parents: Yuanbo Xiong and Xuhui Chen, my lasting spiritual home.

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Chapter 1

Introduction

1.1 Rationale

Departure time choice is an important component of the travel decision-making process. Understanding the factors and behavioral mechanisms that determine travelers' departure time choices is a prerequisite to designing and evaluating policies aimed at mitigating congestion and reducing emissions.

With a great number of vehicles traveling on the road especially during the peak hours, the congestion level of Washington D.C.'s major corridors, including the Capital Beltway (I-495), I-270, and I-95, is far from satisfactory. In response to the changing congestion pattern and travel condition, naturally, commuters may deviate from their habitual departure time to avoid extreme delay in peak hour and/or to avoid being late. In this regard, travelers' preference toward alternative departure times is an important dimension for travel demand and policy analysis when peak spreading is of concern.

Multiple congestion management initiatives have received increased attention recently including dynamic tolling and managed lanes, due to their efficiency in altering travelers' departure time and route choice [3]. Time varying charges influence trip makers to make departure timing decision so as to minimize their associated travel cost. Managed lanes such as HOV/HOT lanes can move at full speed even

when parallel lanes suffer delays from queuing, which also play an alternative role of avoiding peak congestion. The consideration of trip timing behavior is essential for modeling the impact of congestion pricing and any other scenarios corresponded to peak spreading and dynamic route/lane choice. Thus, the ability to realistically capture trip makers' response to time varying road charges is essential for predicting network flows under dynamic road (congestion) pricing.

However, traditional four-step transport planning models and traffic operations models usually neglect the within-day temporal dynamics of the travel demand, only focusing on getting the average travel pattern. In the state of Maryland, several effective modeling tools for traffic analysis and travel forecasting has been successfully developed in recent years. Examples include the I-270 corridor microscopic traffic simulation model and the Maryland Statewide Transportation Model (MSTM). In order to comprehensively analyze the traffic and demand impact of the aforementioned various operations and planning strategies, a fully operational departure time choice model, as well as the integration of traffic models and travel demand models at the corridor, multi-corridor, and even statewide levels, is badly needed.

1.2 Research Objectives

Therefore, the main research objective is to specify, estimate, validate, and demonstrate a fully operational departure time choice model.

The normative behavioral theory, which assumes substantial rationality, com-

plete information, and utility maximization, has been applied extensively in modeling departure time choice as the following chapter of literature review will show. Following this line of research, the thesis first develops discrete choice models and highlights the latent class model which considers heterogeneous taste by specifying different user classes.

Then the thesis alternatively develops a novel positive approach to departure time choice modeling, which considers the role of Search, Information, Learning, and Knowledge (SILK) in travel decision-making, and focuses on how departure time decisions are actually made. Departure time choice is theorized as a continual search process with several key concepts defined and operationalized including spatial-temporal travel knowledge, adaptive learning, subjective beliefs, subjective search gain, perceived search cost, search starting and stopping conditions, search rules, and decision rules.

In practice, there is imperative need for incorporating departure time choices into both microscopic traffic operations analysis and micro/macro-level travel demand studies. For instance, short-term congestion management strategies including peak-period pricing, traveler information systems, and operational improvements often induce departure time shifts and peak spreading (i.e. trips diverting from peak to off-peak, and from peak-peak to shoulder-peak period). Long-term travel demand growth will likely cause even worse congestion during peak travel hours, and subsequently lead to departure time shifts. The proposed positive model tracks the departure time changes of each individual user in the transportation system, and therefore is especially suitable for integration with microscopic traffic simula-

tors, simulation-based dynamic traffic assignment models, and activity/agent-based travel demand models.

Microscopic traffic simulation models exhibit strong advantages in capturing detailed traffic dynamics and have been approved in practice a valuable tool for evaluating corridor capacity expansion and traffic operation improvements. Their applications have recently been extended to address a broader range of transportation-related issues, including congestion management, multimodal corridor improvements, evacuation planning, land use and economic development. However, a comprehensive analysis of many of these issues requires models that can consider various demand responses to these traffic management strategies such as peak spreading, modal shifts, and traffic diversions at the corridor and regional levels, all of which are conventionally taken as given in micro-simulation models. Another challenge for applying micro-simulation models to large network is due to the difficulty of obtaining reliable travel demand data (usually as time-dependent origin-destination matrices).

Although planning models are traditionally used to address these demand-side problems, they are criticized for:

- Assigning traffic flow over link/corridor capacity;
- Lacking the ability to output micro-level performance measures; and
- Being unable to capture the impact of policy changes and/or operational improvements such as better signal timing.

As planning models move from the aggregate four-step models into more realistic

individual-based models, more details on travel experience (e.g. time-dependent travel time) are required to make these models operational in practice. Surveys based on hypothetical scenarios, which are heavily relied on during the model development and calibration process, can only support analysis for a limited number of OD pairs due to budget and man-power constraints. However, these inputs can be easily extracted from microscopic traffic simulation models. Naturally, it becomes very attractive for both researchers and practitioners to develop integrated models to benefit from strengths of both sides. Therefore, this thesis also puts considerable effort into taking all the advantages of the traffic simulators while applying the departure time choice models.

1.3 Contributions

This thesis focuses on the development of a fully operational and theoretically sound departure time choice model. And at the mean time, it aims at testing the feasibility of integrating the behavioral model to traffic models in order to analyze traffic operations, route diversion, peak spreading, and other major demand shifts under a variety of traffic operations and planning scenarios. Compared with previous studies, this thesis has made contribution in the following aspects:

Firstly, the thesis explores the discrete choice models and highlights the merits brought in by the latent class modeling, which is largely unexploited in travel behavior research. Compared with mixed logit, the latent class model relaxes the strong assumption regarding the parameter distribution and performs statistically

as good without consuming as much computational time as mixed logit since the latter often requires a number of simulation draws.

Secondly, the thesis recognizes the limitations of the normative approach and develops a novel positive approach to model the departure time choice. This model considers the drivers' actual behavior rather than the behavior that maximizes the utility. Overall, it successfully removes the assumption about perfect information and utility maximization. Each individual can only identify finite departure time alternatives in the model, which addresses the limitation regarding the unrealistically large alternative set. In addition, the heuristics and rules derived in this approach are extracted from behavioral data. They are intuitive and can easily be implemented in micro-simulation. The extra information necessary for estimating this model is gathered by a carefully designed retrospective recall survey questionnaire.

Finally, the thesis demonstrates the idea of integrated behavioral and traffic simulation model based on a real world application. This is one of the earliest research attempt to consider rich behavioral response in the multi-corridor planning and operations modeling. One of the strengths of the rule-based positive departure time choice model is that the execution of the rules requires minimum computational resources, which makes the micro-simulation, which involves a large number of decision agents, computationally feasible.

1.4 Outline of Thesis

The remainder of the thesis is organized as follows.

In Chapter 2, the literature related to the departure time choice modeling is reviewed and discussed thoroughly. Two behavioral theories are contrasted, i.e. normative theory and positive theory. Normative theory assumes perfect information and maximizes the random utility. And it is applied in two lines of research, including equilibrium scheduling theory and discrete choice analysis. Positive theory focuses on what individuals actually behave and relaxes the strong assumptions of rationality. The work that combines the departure time choice models and traffic models is also reviewed in this chapter.

In Chapter 3, we present the survey design and data collection procedure. To estimate the departure time choice models, a web-based joint stated preference (SP) and revealed preference (RP) departure time, mode/lane choice, and departure time search survey has been conducted in the year of 2011. It consists of two waves of data collection collecting a total number of 151 effective samples.

In Chapter 4, three discrete choice models based on rational normative theory are presented. A latent class study is highlighted here for its unique capability of representing the behavioral heterogeneity without assuming unwarranted distribution of random parameters. The latent class model reveals drivers' latent preference towards sharing ride (i.e. carpooling using high-occupancy vehicle lane). It further reveals that this latent preference is associated with age and whether they are currently carpooling or not. Thus, the taste variation is represented by the two latent classes, with one class preferring carpooling.

Chapter 5 develops a novel positive approach to model the departure time choice, focusing on how the departure decisions are actually made. The choice is

theorized as a continuous search process with several key concepts defined and operationalized including spatial-temporal travel knowledge, adaptive learning, subjective search gain, perceived search cost, search starting and stopping conditions, search rules, and decision rules. A numerical example highlights that the proposed positive model tracks the departure time changes of each individual user in the transportation system and is able to estimate rich behavioral dynamics, such as day-to-day evolution of congestion by departure intervals and individual-level learning, search, and decision-making processes over time.

Chapter 6 demonstrates the positive model's suitability for integration with microscopic traffic simulators. This integrated model covers three inter-state freeway corridors (i.e. I-270, I-495, and I-95) in the Northern Washington D.C. metropolitan area, capturing the regional impacts of new policies and infrastructure development. Firstly, a large-scale traffic micro-simulation model has been built and calibrated. Then the integrated modeling framework is developed and tested on a designed scenario. With this valuable tool, regional and corridor-level planning analysis is able to capture temporal demand dynamics in a more accurate manner.

Chapter 7 provides the conclusion to the thesis.

Chapter 2

Literature Review

2.1 Overview

Conventional four-step planning models usually neglect the within-day temporal dynamics of the travel demand, only focusing on getting the average travel pattern. However, the severity of road congestion also largely depends on the distribution of travel demand among different time periods of the day. Thus, understanding how people schedule their trips becomes very crucial in managing congestion and making policy/planning decisions. The study of departure time choice has started as early as half century ago. From then on, researchers have investigated this interesting scheduling behavior from various aspects, either formulating it as a supply-demand equilibrium problem, or discretizing the time axis and empirically modeling it as a choice based on random utility theory.

This chapter reviews comprehensively the literature world of the departure time studies, as well as the applications of the departure time models in various planning/operations analysis. Firstly, the materials based on utility maximization theory are summarized. This line of research is often referred as the “normative” approach, being prescriptive and making claims about how the individuals should behave. On the other hand, the descriptive “positive” approach also exists. And it claims about how the individuals actually behave. While this positive behavior

theory is seldom seen in modeling departure time choice and other travel behavior, a thorough interpretation of the theory is provided. In particular, travelers' relevant spatial-temporal knowledge, subjective beliefs, search process, and decision making are within the theoretical framework. Lastly, the relevant integrated models are reviewed, which typically involves dynamic traffic assignment (DTA) models and/or traffic micro-simulators. This chapter paves a solid background of the thesis. The contribution made by the thesis in advancing both the state-of-the-art and the state-of-the-practice is also highlighted in this chapter.

2.2 Utility Maximization Theory

Rational behavior theory assumes that individuals can identify all feasible alternatives, measure all of their attributes, and choose the alternative that maximizes their utility (Von Neumann *et al.* [79], Samuelson, [65], Savage, [66]). There have been extensive research efforts applying this approach to departure time choice analysis. In particular, some earlier studies have adopted the following utility function $V(t)$ with respect to departure time t :

$$V(t) = \alpha T(t) + \beta \max(0, (PAT - t - T(t))) + \gamma \max(0, (t + T(t) - PAT)) \quad (2.1)$$

Where, $T(t)$ is the travel time associated with departure at time t ; PAT is the preferred arrival time at destination; α , β , and γ are parameters to be estimated. In addition, the departure time choice set may be assumed to be either continuous (i.e. infinite number of options) or discrete (i.e. several predefined departure time intervals).

2.2.1 Equilibrium Scheduling Theory

Vickrey [78] examined a single bottleneck and derived supply-demand equilibrium conditions with departure time considerations. Inspired by Vickrey’s seminal contribution, several researchers, including Arnott *et al.* [3], de Palma *et al.* [23], and van Vuren *et al.* [77], have developed continuous departure time modeling frameworks, collectively referred to as the “Equilibrium Scheduling Theory” (EST). Later, EST was integrated with route choice analysis (Mannering [49], Mahmassani *et al.* [48]). Bates [7] and Hague Consulting Group *et al.* [37] employed EST for network-level transportation models and for dynamic traffic assignment. The HADES (i.e. Heterogeneous Arrival and Departure times based on EST) model represents the latest achievement of the EST-line of research.

2.2.2 Discrete Choice Analysis

The second line of research based on rational behavior theory focuses on discrete departure time choice modeling. Small [70] adopted the multinomial logit (MNL) approach to model departure time decision-making. However, the underlying assumption of independence from irrelevant alternatives (IIA) in MNL may not hold for departure time choice analysis because adjacent departure time options tend to exhibit correlated unobservable factors. In other words, if a decision-maker prefers departure interval t , the same decision-maker probably also prefers departure time intervals $t-1$ and $t+1$ to other intervals due to some unobservable factors (e.g. dropping off/picking up a child as part of the trip, unknown scheduling constraints).

Various methods for relax the IIA assumption have been proposed by researchers in subsequent studies.

Nested logit (NL) models have been used to identify and address the correlated departure time intervals (Polak and Jones [57], COWI *et al.* 1997, Browman *et al.* [16]). Small [71] and Bhat [13] both tested the NL and a more general ordered generalized extreme value (OGEV) model, which allows for a correlation parameter, for a pair of alternatives, depending on the distance between these alternatives along some natural ordering such as the clock time in departure time choice. And they concluded that both the NL and the OGEV models performed better than MNL. More recently, Ozbay and Yanmaz-Tuzel [55] estimated the NL model based on SP data to evaluate the New Jersey Turnpike time-of-day pricing program. In the model, the upper nest represents transponder ownership and the lower nest represents departure time choice. Their departure time choice is categorized into three alternatives: pre-peak, peak, and post-peak period. The contribution of this study is the value of travel time (VOTT) estimation for a specific user influenced by departure/arrival time in the presence of time-of-day pricing applications.

An even more general approach in identifying correlation parameter is the paired combinatorial logit (PCL) model. The PCL model allows for different correlation between each pair of alternatives; however, the correlation factor does not depend on the distance between the alternatives as in the OGEV model. Koppelman and Wen [44] developed paired combinatorial logit (PCL) model based on the inter-city mode/departure time choice data from the Toronto-Montreal corridor in 1989. Their result indicated that PCL with paired structure provides the best statistical

fit compared to MNL and NL. The PCL was shown to provide a better prediction on direct and cross elasticities compared to MNL and NL models.

Cross-nested logit (CNL) models, which allow more flexible substitution patterns than NL, were also explored by researchers, including Vovsha [80], Ben-Akiva and Bierlaire [8], Wen and Koppelman [81], and Papola [56]. More recently, Lemp *et al.* [45] introduced the continuous cross-nested logit (CCNL) model, which considers correlations across alternatives in a way similar to the continuous response variable approach but still retains the random utility theoretical framework. This approach takes advantage of the ease of the application of random utility theory and recognizes the continuity in time.

Another line of discrete choice research focuses on the mixed logit (ML) models with random-coefficients and/or error components. Bhat [12] and de Jong *et al.* [22] adopted the error components logit (EClogit) specification, taking into account the different degrees of substitution among departure time intervals. Borjesson [15] developed a mixed logit model considering three alternatives (two for autos and one for public transit) using joint stated preference (SP) and revealed preference (RP) data. ML models are highly flexible that they can approximate any random utility models [51]. However, they are often criticized for requiring the analyst to make specific assumptions about the distributions of parameters across individuals [36].

Unlike the ML which assumes specific distributions of parameters, the latent class (LC) models capture unobserved preference heterogeneity by assuming that dividing the population into a discrete number of classes can sufficiently represent the taste variation [67]. Greene and Hensher [36] and Shen *et al.* [67] compared LC

and ML and raised the special merits offered by the LC models. The LC models are often used in marketing research, while there are few studies in transportation. Very recently, Ben-Elia *et al.* [11] applied LC based on the notion of a latent preferred arrival time to study the reward effect on peak-hour avoidance. Based on the LC specification, they drew interesting conclusions regarding the latent heterogeneity in arrival time preference.

2.3 Positive Behavior Theory

Most previous studies have adopted the utility maximization and perfect information assumptions of rational behavior theory. Tversky and Kahneman [76] argue on the basis of a number of empirically studies that individuals rely on mental shortcuts or heuristics that “are highly economical and usually effective but lead to systematic and predictable errors.” This is especially true when making choices among a large number of alternatives (e.g. departure time choice) because individuals obviously cannot obtain complete travel time and travel reliability information for every feasible departure time interval. Ettema *et al.* [30] developed a model for departure time and route choice analysis, wherein individuals update their knowledge about traffic conditions based on their respective travel experience. The CHAID decision tree algorithm was used to model departure time choices based on learned travel time and travel uncertainty information. Utility maximization is still assumed in the modeling framework, and therefore their method is probably better described as a hybrid modeling method.

In reality, an individual’s knowledge about the travel condition of different alternative departure time choices is obviously incomplete and often biased. Each traveler actually accumulates the travel experience day by day and gradually forms spatial knowledge through the learning process, according to the nature of spatial knowledge interpreted by Golledge and Stimson [34]. Thus, explicitly modeling this spatial learning and knowledge accumulation process becomes crucial in a positive model which aims at modeling what the travelers actually behave. Bayesian learning has been applied in several route choice studies (Iida *et al.* [40], Jha *et al.* [41]) which model route perception and travel time learning without considering the complete spatial-temporal knowledge. Other methods such as latent variables [60], measurement of functional hierarchies [4] have also been employed by researchers to model network knowledge.

There are at least two general theories of human behavior that do not assume substantial rationality: prospect theory [42] and bounded rationality theory [68]. Based on the prospect theory, values are assigned to gains and losses. Decision-makers use subjective and biased weights to replace probabilities in knowledge representation and decision-making. The bounded rationality theory suggests that decision-makers must spend time, money, and mental efforts to obtain information and evaluate options, and their goal of utility maximization is bounded by the resulting incomplete information and human computational capabilities. In the end, individuals exhibit satisficing behavior instead of true utility maximization. Other decision-making paradigms such as dominance, elimination by aspect, and lexicographical rules all suggest that individual may adopt heuristics in decision-making,

especially when they need to select from a large number of alternatives (Slovic *et al.* [69], Svenson [73], Ben-Akiva and Lerman [10]).

Researchers have long realized that the assumption of a full choice set is often unacceptable and thus devoted themselves to improving the behavioral realism of the choice set generation process (Manski [50], Swait and Ben-Akiva [74], Ben-Akiva and Boccara [9], Cascetta *et al.* [17]). The choice set generation process in the context of departure time analysis is the search for alternative departure times, which is often assumed away in previous research. Search theory, originally developed in economics (Stigler [72], Salop [64], Rothschild [62]), may be applied for departure time choices. It theorizes the process in which individuals search for alternatives with various behavioral and environmental constraints. In contrast with the obvious relevance of search theory to travel decision-making, few travel behavior studies have applied this theory (Timmermans [75], Richardson [61], Williams and Ortúzar [82]). Mahmassani and Chang applied a boundedly rational search process [47], using the notion of indifferent bands to theorize travelers' satisficing behavior under imperfect information. But they did not fully specify search starting and ending conditions with concepts such as search gain and search cost.

As individuals identify new departure time alternatives from the search process, they need to decide whether or not they will use the new alternatives. This requires a set of decision rules in departure time models. While maximizing utility acts as the decision rule for rational behavior analysis, positive departure time models need to focus on how individuals actually make departure time choice decisions. Several knowledge representation methods, such as machine learning and

logical programming, can estimate a set of decision rules based on observed decision outcomes and decision environment (Durkin [28], Arentze and Timmermans [2]).

Building on previous theoretical and experimental human behavior research in other fields, Zhang [85] developed a positive theoretical framework (referred to as the SILK theory) for travel decision-making analysis, which was subsequently applied to model route choices on a real-world transportation network. The framework explicitly considers learning, knowledge updating, belief/expectation adjustment, search process, and decision rules.

2.4 Integrated Models

Although planning models are traditionally used to address the demand-side problems, they are criticized for: (1) assigning traffic flow over capacity and (2) unable to capture operational improvements such as better signal timing. As planning models move from the aggregate four-step models into more realistic individual-based models, more details on travel experience (e.g. time-dependent travel time) are required to make these models operational in practice. Surveys based on hypothetical scenarios, which are heavily relied on during the model development and calibration process, can only support analysis for a limited number of OD pairs due to budget and manpower constraints. However, these inputs can be easily extracted from microscopic traffic simulation models. Therefore, it becomes very attractive for both researchers and practitioners to develop integrated models to benefit from strengths of both sides.

The integration of microscopic traffic simulation with demand models has been proposed for years. For example, Antoniou et al. [1] introduced a demand simulation tool for DTA models, in which the departure time choice is determined within a more general trip decision structure. The departure time was divided into five intervals: depart two intervals earlier; depart one interval earlier; depart on her/his preferred time; depart one interval later; depart two intervals later. The analysis in this thesis follows his choice-set structure with the interval length pre-set as 20 minutes. Several years after Antoniou, Esser and Nagel [29] studied the home-based work trips in Portland, Oregon by implementing a systematic feedback between demand generation and traffic simulation. Route and destination decisions are considered and the objective is to match the overall commute time distribution. The demand model lacks behavioral foundation and explicit departure time choice is not considered.

Recently, a number of studies have been conducted to combine Dynamic Traffic Assignment (DTA) models with advanced demand models (e.g. activity-based models). Examples include Miller and Roorda [53], Lin *et al.* [46], and Hao *et al.* [39]. These studies generate activity patterns from synthesized travelers. And then the travel demand is dumped into simulation-based DTA models to decide traffic pattern, which will in turn be fed back into the activity generator. This iterative process is repeated until a convergence in behavior is reached. Departure time is selected from pre-determined sets for each individual. Most of these models are calibrated against aggregate travel demand instead of individual behavior. In contrast, Flötteröd *et al.* [32] explicitly modeled learning behavior in travel “plan” genera-

tion. In a more recent study, Flötteröd *et al.* [31] further discussed the calibration of behavioral model parameters (such as the coefficients of a utility function) from traffic counts. Two previous studies are specifically centered on departure time choice problem in integrated modeling framework. De Palma and Marchal [24] modeled the aggregate probability of departing during each time slot for each OD pair by applying Vickery’s model, while Ettema *et al.* [30] use a mental model to describe the effect of learning and adaptation processes on departure time decisions. As mentioned, Ettema’s model also provides a good example considering individuals’ learning and adapting behavior.

Two major limitations of the existing integrated models that are worth noting are identified by the author here. Firstly, previous studies exclusively follow the utility maximization paradigm in describing individual responses to traffic condition changes. As discussed in the previous section, however, many researchers [5] criticize random utility maximization, arguing that it describes how travelers should behave instead of how they actually behave. It is crucial to realize that people are limited to either knowledge about ever-evolving network conditions and willingness or capacity to optimize their travel decisions. Many behavioral studies suggest that decisions are guided by simple rules rather than a complex evaluation process [34]. Secondly, most previous studies focused on integrating travel demand models with microscopic simulation are either limited in scale (e.g. only one corridor is modeled in Ettema’s model [30]) or not detailed enough to capture impact of traffic operation improvements (e.g. DTA-based analysis cannot model traffic signal with sufficient detail). These two limitations are discussed and partially addressed in this thesis.

2.5 Summary of the Literatures

Overall, departure time choice is still an immature area, in which none of the models is well accepted. The current departure time choice research is classified here into two types: first, the studies developing continuous departure time modeling within the EST framework; second, the studies that discretize the departure time and apply discrete choice models based on random utility theory. These two types of models can be together referred as the normative approach which assumes individual rationality and maximizes random utility. Much research effort has been put on this line of studies. CNL and CCNL models have been developed to address the issue regarding the correlation among the different choice alternatives in the large departure time choice set. Random parameters and error components have been employed in ML and EClogit models to address the issue regarding individuals' taste variation.

When dealing with heterogeneity and taste variation, the strong assumption made in ML and EClogit models that certain parameters follow certain distribution(s) often lacks credibility. The LC model, while semi-parametric, frees the modelers from possibly strong or unwarranted distributional assumptions about individual heterogeneity. Moreover, with the specification of a class probability model within the LC, the model's accuracy can be further improved. However, this type of model specification is seldom tested in departure time studies. The thesis develops a LC model, as well as a mixed logit model, in the Chapter 4, taking the latent carpooling preference into consideration.

While some researchers criticize utility maximization theory for representing what travelers should do instead of representing what they actually behave, the author reviews research work regarding the positive theory, including knowledge representation, Bayesian learning, and search theory. An innovative positive model can be found in the Chapter 5 applying the other school of methods: positive modeling theory, wherein the imperfect information is assumed and the decisions made by travelers are guided by simple heuristics. Obvious merits of this approach include its relaxation of the strong assumption regarding perfect information, its intuitive representation of human decision heuristics, and the unique simplicity that it offers to agent-based/activity-based demand models and simulation-based traffic models. The last point of its merits is fully interpreted in the Chapter 6 using a case study designed with microscopic traffic simulator.

Chapter 3

Survey Design and Data Collection Procedure

3.1 Overview

In the previous chapters, the need of analyzing peak spreading or departure time switching has been highlighted. And the existing literature on modeling this phenomenon has been summarized. Based on the literature review, the common limitations in previous works have been recognized by the author. One major research gap lies in the linkage between the behavioral models and traffic simulation models, as well as in the development of a feasible tool that can be efficiently implemented in large-scale simulation process.

To initiate the development of the departure time choice model and the integrated traffic simulation model, Maryland State Highway Administration (SHA) and University of Maryland conducted a web-based joint stated preference (SP) and revealed preference (RP) departure time, mode/lane choice, and departure time search survey. It consists of two waves of data collection collecting a total number of 151 effective samples. The first-wave survey was conducted on March 21-25, 2011, the second one being conducted on May 23-27, 2011.

The survey questionnaire consisted of two parts. The first part was a list of RP questions about the current travel behavior of respondents and their socio-economic status. The second part contained an SP experiment, which used the answers given

to the RP questions to determine the values of attributes presented to respondents.

3.2 Sampling and Data Collection

The survey used simple random sampling method. The population from which the respondents were recruited consisted of car drivers traveling on the Capital Beltway in the Washington DC metropolitan area during weekday morning and afternoon peak period (6:00 a.m.-10:00 a.m., and 3:00 p.m.-7:00 p.m.). Drivers were intercepted during their journeys when they were waiting at traffic lights on several off-ramps of the Beltway. A flyer designed for this study was distributed to the drivers, and the link to a web-based joint revealed/stated preference survey on departure time and lane/mode choices was provided in the flyer. 2,200 drivers had been reached by the research team during the data collection period. And 173 drivers responded the survey questionnaire, which results in the overall response rate of 7.9%. Within the 173 responded surveys, 80 of the respondents completed the survey, which results in the effective sample size of 80 observations.

The 2nd-wave survey used the same sampling method and data collection procedure as the 1st-wave survey. 1,800 drivers had been intercepted and 131 responded the web-based survey, which results in the overall response rate of 7.3%. 71 respondents completed the survey and thus made the final sample size of the two consecutive waves of survey adding to 151 observations. Figure 3.1 compare the distributions of age and income of the final sample with those from the 2010 U.S. Census. In general, the sample is representative of all drivers in the study area in

terms of gender, age, ethnicity, with slight oversampling of higher-income drivers (typical for web-based surveys). Descriptive statistics are presented in the Table 3.1.

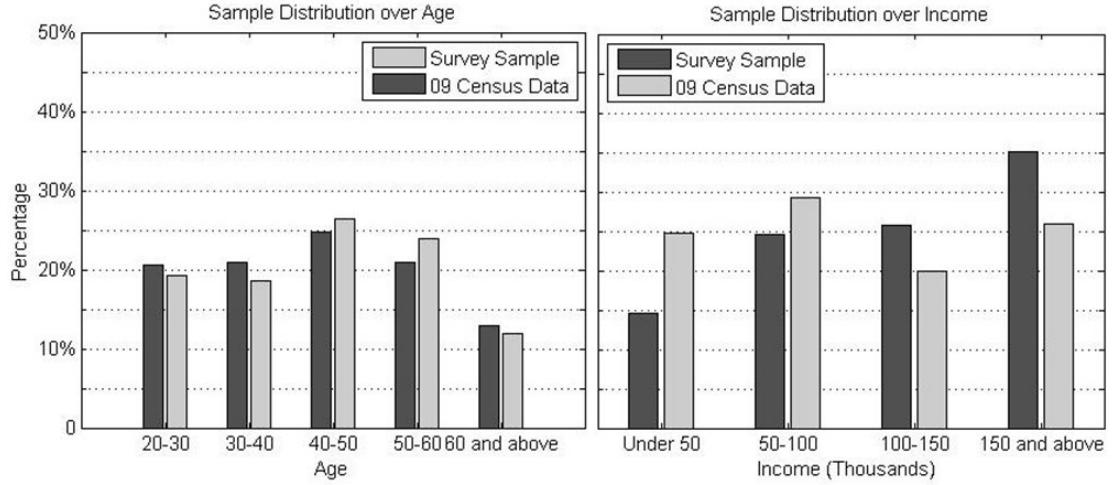


Figure 3.1: Comparison of the Distributions of Age and Income

3.3 Revealed Preference

The RP questionnaire consisted of two sections: respondents' socioeconomics and recent trip information. In the first section, the drivers' gender, age, household income range, education, occupation, number of workers per household, number of vehicles in the household, vehicle type, vehicle age, and work place ZIP code information has been collected.

The second section gathered data about the drivers' most recent trip on the Beltway. The purpose of this section was to use their experienced trip condition as the pivot point when designing the stated preference (SP) questions. This ensured that the stated scenario in the SP part was realistic for each individual in the survey.

Table 3.1: Descriptive Statistics

Variables	Description	Mean	Std. Dev.
Individual Summary Statistics			
<i>gender</i>	Dummy= 1 if the respondent is male	0.5	0.5
<i>age</i>	The respondent's age	43.85	13.26
<i>workers</i>	Number of workers in the household	1.76	0.64
<i>cars</i>	number of vehicles in the household	1.98	0.87
<i>income</i>	Household income	\$50K - \$100K	-
Most Recent Trip Statistics			
<i>TT</i>	Travel time (minute)	33.91	66.95
<i>FC</i>	Fuel cost (\$)	6.24	10.63
<i>distance</i>	Travel distance (mile)	28.56	57.38

The respondent was asked to recall and describe his/her most recent trip information on the Beltway via the following constructs:

- General information (mode, number of passengers, trip purpose, work starting/ending time, and schedule flexibility);
- Trip time (departure time, arrival time, preferred departure time, and preferred arrival time);
- Trip cost (fuel cost, toll cost, park cost); and
- Travel uncertainty information (experienced shortest and longest total travel time, the shortest and longest time spent on the Beltway)

3.4 Departure Time Search Recall Questionnaire

Secondly, a series of carefully designed memory-recall questions were employed to gather behavior process data related to the search for alternative departure times. Each respondent was asked to recall the order of alternative departure times they had considered and actually tried, as well as the travel conditions corresponding to those departure time choices. The distribution of the number of alternative departure times considered is illustrated in the Figure 3.2.

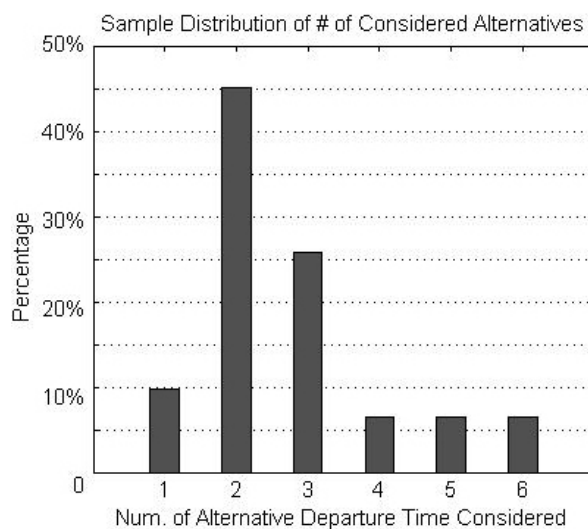


Figure 3.2: Sample Distribution of Number of Alternatives Considered

About 10% of the respondents had only experimented with just one departure time, while most individuals had considered two to three departure times. About 20% of the respondents had tried more than four departure times. In the subsequent modeling section, the reported departure time search characteristics and reported travel conditions (travel delay, schedule delay early or late, etc.) are used to empirically model both the search process, search rules for identifying new alternative

departure times, and the distribution of perceived search costs among commuters.


3.5 Stated Preference

The third and final part of the survey is based on stated preference (SP) design, wherein the respondents were asked to make choices in seven hypothetical choice situations. Unique SP alternatives were designed for each respondent based on her/his reported current commuting trip attributes in the RP part of the survey. Information collected in this part of the survey was used in the following chapters to estimate both the departure time choice utility functions and the departure decision rules that commuters employ to select departure times after they identify alternatives from the search process. Each choice situation included three departure time alternatives with different travel delay, schedule delay, and monetary costs: (1) solo driver on normal lane, (2) high occupancy toll (HOT) lane, and (3) high occupancy vehicle (HOV) lane. Figure 3.3 shows the interface of the departure time choice on the website. As illustrated in Figure 3.3, each alternative is specified with five variables, each of which has up to five levels of variation per alternative. The variables included in the departure time choice experiment includes: (1) Departure time, (2) Travel time range, (3) Arrival time range, (4) Fuel cost, and (5) Toll. These variables are designed to account for traffic conditions by time of day taking into account the observed respondents' departure time [21]. The description of the variables used in the SP scenarios is as follows:

- Departure time: Departure time is pivoted from respondents' reported depart-

Capital Beltway – HOT Lanes

A survey about travel on the Maryland section of the Capitol Beltway (I-495).



Question 26.

The following travel options are available for your trip along the Capitol Beltway. Your trip is from Exit 36 to Exit 25.

	Normal Travel Lane	SOV Lane (No Passengers)	HOV Lane (Passengers)
Departure Time	8:40 AM	7:40 AM	7:40 AM
Travel Time	45 - 75 mins	30 - 40 mins	30 - 40 mins
Fuel Cost	\$3.90	\$3.30	\$3.30
Toll Cost	\$0.00	\$3.84	\$0.00

Which travel option would you prefer for your trip?

☐ I Will Use the Normal Travel Lanes.
☐ I Will Use the SOV Lane (Single-Occupant Vehicle)
☒ I Will Use the HOV Lane (High-Occupancy Vehicle)
☐ I Will Not Use the Beltway (I will use an alternate route)

Figure 3.3: Departure Time Questionnaire Interface

ture time in the RP.

- Total travel time range: This variable is designed to account for both time-of-day conditions based on the respondents' reported departure time and travel condition on toll lane. It is aimed at capturing travel time uncertainty.
- Arrival time range: This variable is calculated corresponded to the departure time and travel time range of the scenario provided to the respondent.
- Fuel cost: The fuel cost is designed to reflect higher expenses in the peak period and on the normal lane. The fuel cost is pivoted from the reported fuel cost in the RP part.
- Toll cost: The toll cost is designed as a mileage based using the Intercounty Connector toll rates as a reference. The toll rate for the HOT lane accounts varies depending on whether the respondents' reported departure time is in

the peak or non-peak period.

The survey is designed with orthogonal design approach where numerical evaluations in a wide range of parameters values was undertaken to guarantee sufficient efficiency of the design. The pilot study, in combination with expert judgments, was also used to arrive at the final levels of attribute in the SP experiment. The questionnaire design of departure time choice game is shown in Appendix A. The variable lists can be found in Appendix B.

3.6 Limitation/issues

One major limitation of the combined two-wave departure time and mode/lane choice survey dataset is that the survey response rate is relatively low (about 8%). And as shown in the Section 3.2, when compared with the values of all potential participants, the survey respondents' education and income level is slightly higher. These may possibly be the evidence of the non-response bias and therefore further tests for this bias are necessary. For instance, those who didn't answer the web survey should be reached and given a small number of questions. After judging if their answers differ significantly from those who have responded the survey or not, we can determine whether or not there is non-response bias. Once the tests prove the existence of the non-response bias, the method of weighting adjustments should be employed to deal with the low response rates as discussed by Groves [38] and Dey [26].

One possible explanation for the low response rate is that this pilot survey

is conducted without any incentives motivating people to respond. Although the weighting technique can be implemented to address the bias issue, the first and most important point is to avoid low response rate in the first place [26]. Many studies focusing on improving web-based survey response rates are readily available in the literature (Deutskens *et al.* [25], Dillman [27], among others). Some well-accepted incentives that we should consider in the future surveys include: charitable giving, lotteries with small prize but a higher chance of winning, enhancing visual elements (such as product images), sending a reminder, identifying the importance of the survey, sharing the results, and so on.

Chapter 4

A Discrete Choice Analysis with Latent Carpooling Preference

This chapter presents a model of departure time choice based on the notion of a latent carpooling preference. The model has been built using the combined revealed preference and stated preference survey data described in the Chapter 3. The author first estimates a conditional logit model to identify drivers' choice of departure time when toll is added. This interim model is then used to generate starting values for a mixed logit model and a new modeling framework assuming latent class in drivers' preference towards sharing ride (i.e. carpooling using high-occupancy vehicle lane). The latent class model suggests the heterogeneity of drivers' behavior. It further asserts that drivers' preference towards HOV lanes is associated with age and whether they are currently carpooling or not.

4.1 Objectives

Multiple congestion management initiatives have recently received increased attention including dynamic tolling and managed lanes, due to their efficiency in altering travelers' departure time choice as well as route choice. Time varying charges influence trip makers to make departure decision so as to either 'buy' desired travel condition or avoid paying extra money by switching departure time. Managed lanes, such as high occupancy vehicle (HOV) and high occupancy toll (HOT) lanes, can

assure that the vehicles on the lane move at a reasonable speed even when the parallel lanes suffer delays from queuing. This also plays an alternative role of avoiding peak hour congestion. Obviously, these pricing schemes and congestion management tools greatly influence the choice of departure time, and thus should be modeled very carefully.

This chapter develops discrete choice models investigating the impact of various congestion management policies such as tolling and managed lanes. We first estimate several interim models to identify travelers' choice. And then these interim models are used to generate starting values for a new modeling framework assuming latent class (LC) in carpooling preference.

4.2 Models

4.2.1 Data Preparation

The departure time can only be modeled in a binary choice pattern, since in each observation the departure time is generated randomly, shifting 20 or 40 minutes earlier or later than the habitual departure time. Thus, the dataset is treated and transformed into a series of binary choices. Take the Figure 3.3 as an instance. Without loss of generality, let's denote the three alternatives as A , B , and C , respectively. If this particular respondent has chosen alternative A , then there are two observations generated as: (1) A is better than B ; and (2) A is better than C . It is worth noting that it represents only one observation if alternative B or C has been chosen, since B and C are not directly comparable with the same

departure time. The observations that have chosen to change routes are excluded in the dataset.

4.2.2 Conditional Logit Model

One of the most widely used models is the conditional logit form: $V_{ij} = \beta X_{ij} + \varepsilon_{ij}$ which arises when each ε_{ij} is an independent and identically distributed (iid) draw from the type I extreme value distribution with scale parameter μ . The probability (Equation 4.1) that individual i prefers alternative j takes the well known form [52]:

$$P_{ij} = \frac{\exp(\beta' x_{ij})}{\sum_k \exp(\beta' x_{ik})} \quad (4.1)$$

The conditional logit model embodies the IIA property (which means that the odds ratio for any two alternatives is unaffected by the inclusion of any third alternative). And individual's taste variance is not very well represented since in the random utility function, each explanatory variable has the same marginal utility for each individual. Albeit this method has these two well-known limitations, it is a good starting point to explore the dataset and reveal the econometric nature. Thus we consider the following variables in the utility functions:

- $TT_j = (TT_{\min} + TT_{\max})/2$: mean travel time if choosing alternative j , as provided by the SP survey;
- FC_j : fuel cost if choosing alternative j ;
- TC_j : toll cost if choosing alternative j ;

- $DSDE = \max(PDT - DT, 0)$: departure schedule delay early if choosing alternative j ;
- $DSDL = \max(DT - PDT, 0)$: departure schedule delay late if choosing alternative j ;
- $INC4_TT$: interaction variable for income level 4 ($> \$150K$) and mean travel time; and
- AGE_FC : interaction variable for age (> 45) and fuel cost.

The model has been estimated using the software package STATA. The coefficients of the attributes of the choice model are all significant and with the correct sign.

The results are listed in the Table 4.1.

Table 4.1: Estimation Results for the Conditional Logit Model

Variables	Coefficients	Std. Err.	t-Statistic
TT	-0.022	0.009	-3.389
FC	-0.339	0.147	-4.371
TC	-0.403	0.066	-11.204
$DSDE$	-0.007	0.005	-2.241
$DSDL$	-0.006	0.003	-2.562
$DHOV$	-2.200	0.191	-16.319
$INC4_TT$	-0.017	0.019	-2.421
AGE_FC	0.395	0.174	4.240
# of Obs.	1,457		
Log Likelihood	-707.01		
Pseudo R^2	0.300		

The first five variables are impedances, thus having negative signs. This model shows the different levels of impact resulted from travel time, fuel cost, toll cost, and

schedule delays. *DHOV* is a dummy variable which equals one if the alternative is associated with carpooling mode. Normally, picking up carpoolers is considered as a discomfort, which agrees with its negative coefficient. The rest three variables show different effects of level-of-service on different socioeconomic groups. The coefficient of *INC4_TT* is -0.017, which indicates that travel time has an extra penalty on higher-income group of people. *AGE_FC* shows that when choosing departure time, fuel cost is more influential to younger drivers.

4.2.3 Mixed Logit Model

A random component logit specification has first been investigated to improve the model. This type of models allows for a higher level of flexibility by specifying taste coefficients to be randomly distributed across individuals. Normally distributed coefficients have been tested in the model. The model shows that drivers' taste variation is very significant on the variable of departure schedule delay early (*DSDE*). The estimated results are reported in Table 4.2 with all parameters' signs correct and significant. Compared to the conditional logit model result, a slight improvement has been obtained.

4.2.4 Latent Class Model

Another improvement for the conditional logit model is based on latent class specifications. Many respondents in the survey reported that they have been already carpooling with passengers. Thus, *DHOV* should have different penalties on

Table 4.2: Estimation Results for the Mixed Logit Model

Variables	Coefficients	Std. Err.	t-Statistic
<i>TT</i>	-0.024	0.009	-3.458
<i>FC</i>	-0.325	0.147	-4.008
<i>TC</i>	-0.445	0.066	-10.553
<i>DSDE(Mean)</i>	-0.011	0.005	-2.583
<i>DSDE(Std.Dev.)</i>	0.035	0.011	3.226
<i>DSDL</i>	-0.006	0.003	-2.870
<i>DHOV</i>	-2.201	0.193	-14.680
<i>INC4_TT</i>	-0.017	0.019	-1.822
<i>AGE_FC</i>	0.392	0.176	3.850
# of Obs.	1,457		
Log Likelihood	-703.31		
Pseudo R^2	0.305		

different group of people. For instance, those who are already sharing their ride with others are more likely to keep choosing *HOV* rather than paying the toll. On the other hand, traveling-alone drivers may be penalized more severely by the discomfort of choosing *HOV*. The information whether the respondent was driving alone or not has been recorded by the RP survey questions. Secondly, the author assumes that females are more likely to prefer sharing their ride.

Therefore, the author investigates a latent class logit model. This type of models recognizes latent heterogeneity by classifying individuals into several groups. And thus the taste variation is somewhat realized among individuals belonging to different classes. Thus, the probability that individual i prefers alternative j is defined by the Equation 4.2:

$$P_{ij} = \sum_{c=1}^C Q_c P_{ij|c} = \sum_{c=1}^C Q_c \frac{\exp(\beta'_c x_{ij})}{\sum_k \exp(\beta'_c x_{ik})} \quad (4.2)$$

Where $P_{ij|c}$ denotes the conditional probability that i prefers j , and Q_c denotes

the probability that individual i belongs to class c . The class membership model is estimated as a binary logit choice model. The following variables have been selected to build the class membership model, which is based on the previous work and after corrections of trial and error estimation and clearing out of non-significant coefficients.

- *AGE*: dummy variable for the age (= 1 if age > 45); and
- *CARPOOL*: dummy variable for carpooling (equals 1 if the driver in the RP is recorded having at least one passenger).

Therefore, three latent class logit models have been estimated and the results are reported in the Table 4.3. Model 1 is a full model with 15 coefficients. Model 2 reduces the degree of freedom from 15 to 13 by fixing the coefficient of *DSDE* in the *Latent Class 1* and that of *FC* in the *Latent Class 2* to be equal to zero. Model 3 further reduces the degree of freedom by regulating the coefficients of *DHOV* in the *Latent Class 1* to be equal to zero.

The models have been estimated using NLogit. The coefficients of the variables are all significant and with the correct signs. The coefficients of the class probability model are also significant and with the correct signs. Model 1 seems to be the best in terms of log likelihood and pseudo Rho-squared statistic. Model 2 and 3 put restrictions on the parameters in the likelihood expression that effectively reduce the total number of unknown parameters. Likelihood ratio tests for Model 2 and Model 3 have been conducted. The null hypothesis has been accepted at the 95% significance level and thereby has all the assumptions about the coefficients accepted.

The calculation procedure of the Model 2 is shown by Equation 4.3.

$$\chi_{m2}^2 = -2 \ln \frac{L_{m2}}{L_{m1}} = 0.020 < \chi^2(0.95, 2) = 0.103 \quad (4.3)$$

The class probability model suggests that younger drivers and current carpoolers are more likely to belong to the *Latent Class 1*, which is more sensitive to travel time, fuel cost, and schedule delay late, as shown in the model. *Class 1* has a very low *DHOV* coefficient, which means this class is less penalized by *HOV* mode. The taste variation of toll cost is also shown explicitly in the model. Table 4.4 reports the probability to belong to the class of individuals with a *HOV* penalty for each segment of the population. The average probability that individuals belong to *Class 1* is 11.5%.

The cross tabulation of the conditional logit model, and the latent class model has been examined by the author. The latent class model has a considerable better success rate predicting the outcomes within the sample. The prediction accuracy of the latent class model is 79.00% (1,151 successful predicts out of 1,457 observations), while the accuracy of the conditional logit model is only 71.60%. In terms of log likelihood and pseudo Rho squared statistic, the latent class model also does a better job.

4.3 Summary

This chapter mainly investigates empirical models of departure time choice based on the Capital Beltway travel survey data. This data provides a unique opportunity to analyze departure time choice based on stated preference capturing

individuals' behavior response to road charges and other travel condition dynamics. A conditional logit model, a mixed logit model, and a latent class model regarding carpooling preference have been presented.

The dataset is of high quality since it delivers a substantial amount of variability that has been captured by the two improved models. Heterogeneity in behavior is apparent in the mixed logit model. The random terms of schedule delay early is highly significant, indicating the large degree of variation amongst the drivers. The latent class model is supported by stronger statistical results (on this occasion). It interprets the heterogeneity in another context. The class probability model suggests that younger drivers and current carpoolers are more likely to belong to *Latent Class 1*, whose departure time choice is more sensitive to travel time, toll cost, and fuel cost, as these coefficients are negative and statistically significant. This is an interesting finding, which invokes further exploration of age-specific considerations in incentive-based programs.

Secondly, the model also manifests that compared to *Class 2*, individuals of *Class 1*'s departure time decision are more dependent to schedule delay late and they are more likely to use HOV mode. Aside from avoiding toll charge, using HOV/HOT lanes is also often associated with narrower travel time bandwidth, which means less travel time uncertainty and thus less risk to suffer from extremely high congestion. This result interprets that there exists a group of drivers having more fixed travel schedule and preferring carpooling rather than paying toll to avoid possible extreme delays.

In the future, certain improvements on this study can be foreseen by the

author. Firstly, the complex departure time decisions need for better representation. As a major contribution, individuals' preference towards tolling and HOV/HOT lane is revealed to some extent in the latent class model. Given the richness of the dataset, jointly modeling the lane choice and departure time choice may further enhance the model's ability in this regard as the survey combines multiple dimensions of choices. Secondly, without specifying the departure time periods as the alternatives in the survey, the empirical study ends up using discrete choice methodology where the IIA assumption cannot be avoided. We may build more flexible models such as error component logit and generalized nested logit models to relax the strong assumptions on which our current models heavily rely.

Table 4.3: Estimation Results for the Latent Class Logit Model

Variables	Model 1 Coeff. (Std. Err.)	Model 2 Coeff. (Std. Err.)	Model 3 Coeff. (Std. Err.)
Latent Class 1			
<i>TT</i>	-0.129 (0.023)*** ^a	-0.133 (0.071)*	-0.151 (0.091)*
<i>FC</i>	-0.828 (0.212)***	-0.836 (0.409)**	-0.818 (0.458)*
<i>TC</i>	-1.331 (0.210)***	-1.346 (0.519)***	-1.387 (0.564)**
<i>DSDE</i>	0.002 (0.009)	0 (fixed)	0 (fixed)
<i>DSL</i>	-0.029 (0.008)***	-0.029 (0.016)*	-0.031 (0.017)*
<i>DHOV</i>	-0.453 (0.267)*	-0.446 (0.529)	0 (fixed)
Latent Class 2			
<i>TT</i>	-0.023 (0.007)***	-0.022 (0.005)***	-0.022 (0.005)***
<i>FC</i>	-0.001 (0.054)	0 (fixed)	0 (fixed)
<i>TC</i>	-0.339 (0.039)***	-0.340 (0.025)***	-0.343 (0.025)***
<i>DSDE</i>	0.010 (0.004)***	-0.010 (0.003)***	-0.010 (0.002)***
<i>DSL</i>	-0.005 (0.003)*	-0.005 (0.002)**	-0.005 (0.001)***
<i>DHOV</i>	-3.098 (0.771)***	-3.081 (0.178)***	-3.121 (0.182)***
Class Probability Model			
<i>CONSTANT</i>	-2.374 (0.350)***	-2.406 (0.429)***	-3.253 (1.369)***
<i>AGE</i>	-1.360 (0.563)**	-1.371 (0.496)***	-1.334 (0.466)***
<i>CARPOOL</i>	2.826 (0.771)***	2.844 (0.573)***	2.754 (0.536)***
# of Obs.	1,457	1,457	1,457
Log Likelihood	-681.58	-681.59	-681.91
Pseudo <i>R</i> ²	0.319	0.319	0.319

^asignificance level: * - 90% ** - 95% *** - 99%

Table 4.4: Latent Class Model: Probability to be Penalized by Carpooling

Age	Currently Carpooling?	Probability
> 45	Yes	71.3%
> 45	No	97.7%
≤ 45	Yes	38.9%
≤ 45	No	91.5%

Chapter 5

A Positive Model of Departure Time and Peak Spreading Dynamics

This chapter presents a novel positive departure time choice model under the positive theoretical framework. Several modeling methods that traditionally are not used in departure time choice analysis are adopted for their ability of representing actual behavior and computational efficiency, including Bayesian learning, rule-based knowledge representation, search model, evolutionary analysis, and agent-based micro-simulation.

It is necessary to gather behavior process data for the estimation of the proposed model, though most existing datasets for departure time analysis are cross-sectional and therefore insufficient. As mentioned in the Chapter 3, a practical memory-recall survey method with relatively low respondent burden is also designed in this research and employed for behavior process data collection in a joint reveal/stated-preference survey in the Washington, DC metropolitan area.

Following the introduction of the model, a well-designed numerical example demonstrates the capability of this model in reflecting the peak spreading dynamics and the day-to-day traffic congestion evolution.

5.1 Theoretical Framework

The proposed theoretical framework for positive departure time choice analysis is illustrated in Figure 5.1.

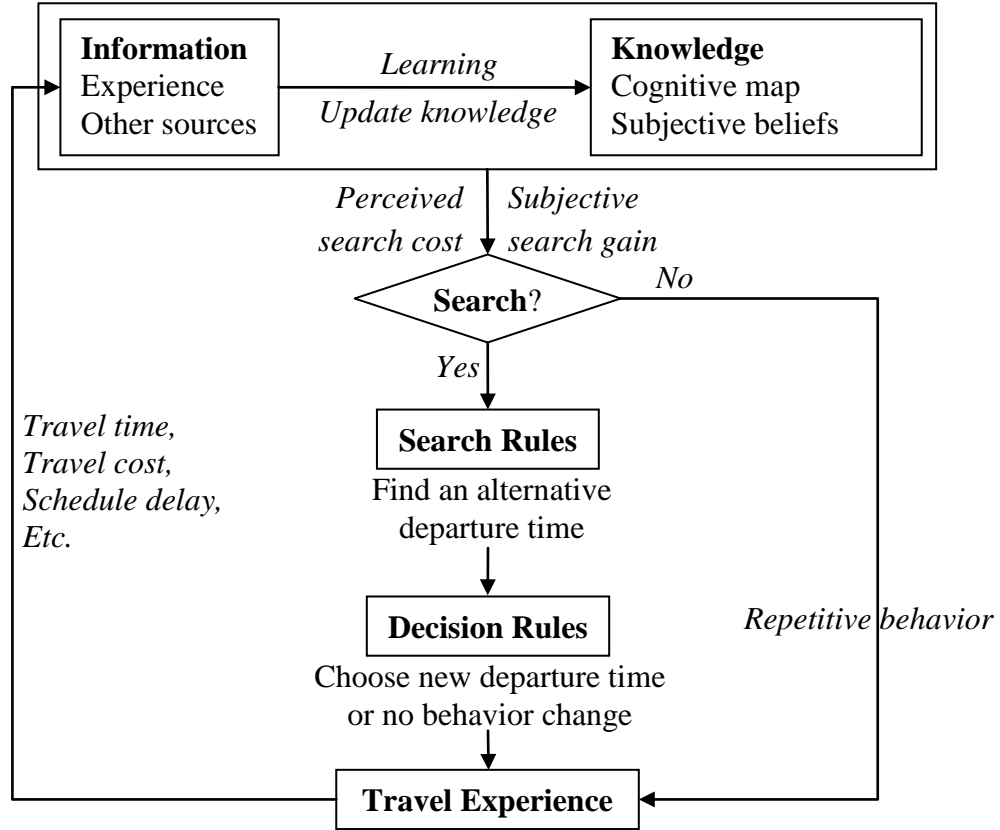


Figure 5.1: Theoretical Framework for Positive Departure Time Choice Analysis

From prior travel experience or other sources (e.g. traveler information systems), an individual accumulates information about travel conditions on the transportation network corresponding to different departure times. Through a perception and learning process which may be biased, the individual forms a certain degree of

spatial knowledge, which produces subject beliefs. For instance, if a person who believes that it is very likely that she/he can find a departure time with less congested traffic conditions and schedule delay, she/he is more likely to start searching for alternative departure times. But after several rounds of search, if the person still encounters severe congestion and/or schedule delay repetitively, her/his subjective beliefs will change and she/he will gradually become content with the best departure time found in previous searches.

To theorize when a person starts and stops searching for alternative departure times, the concepts of subjective search gain and perceived search cost are developed. The subjective search gain is the amount of benefits the person believes she/he can expect to obtain from an additional round of search. It is determined by the person's spatial knowledge and subjective beliefs, and therefore continually adjusted in the search process. The perceived search cost is a personal characteristic that reflects the time, monetary, mental efforts, and/or risk involved in each round of search as perceived by the person herself/himself. The tradeoff between the subjective search gain and the perceived search cost determines when the search for alternative departure times starts and ends (i.e. $\text{gain} > \text{cost}$, start search; $\text{gain} < \text{cost}$, end search). While the subjective search gain can be analytically derived from a person's spatial knowledge and subjective beliefs, the perceived search cost needs to be empirically estimated and is likely to be different for different individuals. This will be discussed in detail in the Model section.

If a person decides not to search, repetitive/habitual behavior is executed. Otherwise, the person will employ a set search rules to identify a new departure

time alternative. The search rules constitute a mapping from spatial knowledge and current departure time to a new feasible departure time. In the positive approach, the search rules should be empirically estimated from observed search processes. It is hypothesized that the search process actually employed by decision-makers are not random, and feasible alternatives are not identified in the search process with equal probabilities. Instead, the search rules may systematically favor certain departure time alternatives. For instance, if a person currently departs at 8 a.m. and is not satisfied with the resulting travel and/or schedule delay, the person may be more likely to try departing at 7:30 a.m. and 8:30 a.m. than 7 a.m. and 9 a.m. (i.e. an anchoring effect). Also, in search for alternative departure times for trips with a preferred arrival time (e.g. work trips), the search process may be biased toward earlier departure times.

If a person decides to search and finds an alternative departure time, she/he needs to determine whether or not to change departure time after experiencing traffic conditions associated with the new departure time. Again in the positive approach, the set of decision rules actually employed by the decision-maker should be empirically derived from observed behavior process data. The decision rules constitute a mapping from spatial knowledge (especially experienced traffic conditions corresponding to different departure times) to a binary decision: choose the new departure time or retain the current departure time. In addition to decision rules, a personal characteristic, better described as patience with new alternatives, also influence the outcome of this decision step. During the trial of a new departure time, a very impatient person may make decisions based on just one observation of the traffic

conditions at that new departure time, while a more patient person may be willing to experience the traffic conditions multiple times before making departure time choice decisions. No matter what the decision outcome is, the decision-maker will nevertheless continue accumulating experience and update her/his spatial knowledge and beliefs.

The proposed theoretical framework considers departure time choice a continuous evolutionary process. If all individuals stop searching for alternatives, the transportation system will reach a “departure time equilibrium”. In contrast, in the normative approach, the departure time equilibrium is achieved when individuals departing from all used time intervals experience equal and maximum utility. The equilibrium derived from the positive approach should be different from that in the normative approach. Therefore, we shall refer to the departure time equilibrium in the positive approach as Behavior User Equilibrium (BUE) to highlight the difference.

5.2 Model

5.2.1 Knowledge and Learning

In this section, Pólya’s Urn model sheds light in the modeling of the human knowledge and learning process. In Pólya’s model, as discussed by Blackwell *et al.* [14] an urn containing balls of I different colors is considered (α_1 balls of color 1, α_2 balls of color 2, etc.). Then N random draws from the urn are performed. The ball is placed back into the urn with an additional ball of the same color after each

draw. As N approaches infinity, the proportions of different colored balls follow a Dirichlet distribution $\mathbf{Dir}(\alpha_1, \dots, \alpha_i, \dots, \alpha_I)$.

This model best illustrates the properties of the process that each individual forms and updates her/his spatial and temporal knowledge. An individual's spatial knowledge for departure time choice is based on experienced utility from previous learning and trials. Due to perception and memory limitation, spatial knowledge and perceived utilities from previous experience are assumed to be stored in I discrete categories. Let n_i be the number of times utility level u_i has been experienced by a particular individual. Therefore, the individual's knowledge about departure times can be quantified as a single-dimension vector $\mathbf{K}(n_1, \dots, n_i, \dots, n_I)$. According to Bayesian learning rules, the perceived weights of past observations are the same. For instance, when a new alternative departure time is experienced and the associated utility falls into category i , the updated knowledge becomes: $\mathbf{K}(n_1, \dots, n_i + 1, \dots, n_I)$. Let vector $\mathbf{P}(p_1, \dots, p_i, \dots, p_I)$ represent an individual's subjective beliefs, where p_i is the subjective probability that an additional search would lead to an alternative departure time with utility level u_i .

Therefore, we assumed that individuals' prior beliefs follow a Dirichlet distribution, which is an n parameter distribution, to establish a quantitative relationship between knowledge \mathbf{K} and beliefs \mathbf{P} . Since the Dirichlet is the conjugate prior of the multinomial distribution, the posterior beliefs will also be a Dirichlet distribution [62]. This assumption is equivalent to assuming Equation 5.1, where N denotes the

total number of observations ($N = \sum(n_i)$).

$$p_i = n_i/N \quad (5.1)$$

Based on this assumption, if an individual has experienced utility level u_i twice out of five previous departure time trials, this individual would believe that the chance of experiencing utility level u_i again in the next departure time trial is $2/5 = 40\%$.

5.2.2 Subjective Search Gain and Perceived Search Cost

The decision to search for a new alternative departure time is based on the relationship between subjective search gain and perceived search cost. Let an individual's utility on the currently used departure time be u . The subjective search gain (g) is based on subjective beliefs \mathbf{P} , and defined as the expected utility improvement from an additional search:

$$g = \sum_{i(u_i > u)} p_i \cdot (u_i - u) \quad (5.2)$$

where u is the maximum of all observed utility levels (u_{\max}) because individuals can be selected from all tried departure times.

Let u^* be the theoretically maximum utility level under free-flow travel condition, and assume all individuals initially believe there is no congestion. As the search process proceeds, the subjective probability of finding a departure time with utility level u^* after N searches is $1/(N + 1)$. Therefore, Equation 5.2 can be further simplified as Equation 5.3. The subjective search gain is always positive since u^* (theoretical maximum) is always higher or equal to u_{\max} (actually experienced

maximum). Equation 5.3 also indicates that subjective search gain decreases when the number of searches increases, and/or when a better alternative is identified (i.e. higher u_{\max}).

$$g = (u^* - u_{\max})/(N + 1) \quad (5.3)$$

In order to model search start and stopping conditions, perceived search cost needs to be empirically estimated and then compared with subjective search gain. Perceived search cost is assumed to be constant for the same individual throughout the search process, but varies across individuals. It represents both the variety-seeking propensity of individuals and the perceived mental/monetary cost associated with search. If we empirically observe that an individual stops searching after n rounds of search, the perceived search cost for that individual must be lower than the subjective search gain after $(n-1)$ searches such that search n is meaningful, and must be higher than the subjective search gain after n searches such that search $(n+1)$ does not occur. These lower and upper bounds of perceived search cost can be calculated using Equations 5.4 and 5.5 respectively. The average of the lower- and upper-bound estimates is taken as the final estimated perceived search cost (c) for the individual (Equation 5.6):

$$c_{LOW} = g_n = \frac{u^* - u_{\max,n}}{n + 1} \quad (5.4)$$

$$c_{HIGH} = g_{n-1} = \frac{u^* - u_{\max,n-1}}{n} \quad (5.5)$$

$$c = \frac{1}{2}(c_{LOW} + c_{HIGH}) \quad (5.6)$$

We also allow perceived search cost to vary for different trips because it may be more different to search for alternatives for certainly trips than for other trips (e.g., trips

with different destinations, distances, and scheduling constraints). The method is to empirically estimate the relative perceived search cost ($c^* = c/u^*$). In order to empirically derive the distribution of relative perceived search cost, information about searched alternatives, the order by which alternatives are searched, and attributes of each alternative departure time was extracted from the memory-recall survey data (Part 2 of the survey described in Chapter 3). The estimated cumulative density distribution function of c^* , as well as its lognormal and Weibull approximations, is plotted in Figure 5.2. From the graph, we can observe that about 80 percent of individuals will search for new alternative departure times for their commuting trips if the subjective search gain exceeds $0.6u^*$, while only 30 percent of individuals will continue searching when the subjective search gain decreases to $0.2u^*$ (i.e. 20% of the theoretical maximum utility from that trip). It is also interesting to find from the empirical estimates that about 5% of individuals will never search for alternative departure times because their perceived search cost is higher than the theoretical maximum utility from that trip (the region where the value on the horizontal axis exceeds 1). The utility function (u) itself is also empirically estimated based on Small's multinomial logit specification [70] using the memory-recall survey data. The function consists of four explanatory variables including travel time, schedule delay early, schedule delay late, and monetary cost. While this term is denoted in this analysis as utility, u is really a measure, in the true behavioral sense, the level of satisfaction associated with various alternative departure times. It is not assumed in the research that individual can maximize utility. Instead, the positive behavior model estimates how individuals try to improve their satisfaction level subject to

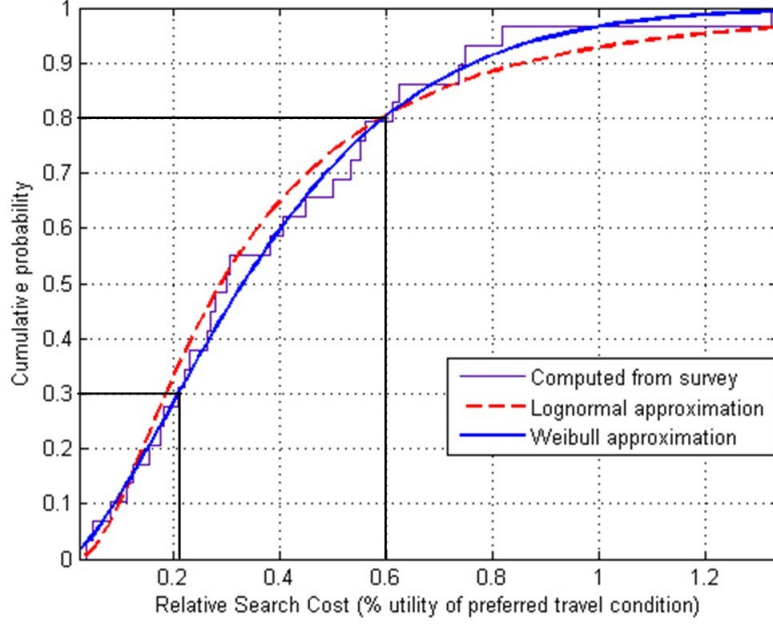


Figure 5.2: Distribution of Relative Search Costs

learning, limited knowledge, perception and belief, and perceived search cost.

5.2.3 Search Rules

Once an individual decides to start searching for alternatives (i.e. subjective search gain becomes larger than perceived search cost due to either new spatial knowledge or external stimuli such as increase level of congestion and/or schedule delay associated with the current departure time choice), the individual employs a set of rules to search alternative departure times, which need to be empirically derived for the positive modeling approach. The search for alternative departure times is obviously not random due to scheduling constraints and anchoring effects. For example, an individual, whose current departure time is 7:30 a.m. with a preferred arrival time at 8:00 a.m., may adjust the departure time when congestion worsens.

It is more likely that this individual will first experiment with alternative departure times closer to 7:30 a.m. (anchoring effect). In addition, it is less likely that this individual will consider departure times later than 7:30 a.m. due to scheduling constraints. To consider these factors, we define departure time alternatives that anchor at the current departure time, e.g., 0–15 min earlier, 0–15 min later, 15 – 30 min earlier, 15–30 min later, and so on. Schedule delay considerations are incorporated into the explanatory variables in the search rules.

If-then rules are selected to represent departure time search heuristics for several reasons because they are shown to be capable of replicating various types of human heuristics and decision-making processes in previous expert systems and knowledge extraction research, and because the execution of if-then rules at the model implementation stage requires minimum computational resources which is important especially for large-scale departure time and peak spreading models involving millions of independent decision-makers.

Part 2 of the survey data on search processes (see Chapter 3) are used to derive search rules. The variables used in the search rule induction model include: arrival schedule delay early ($ASDE$), arrival schedule delay late ($ASDL$), travel time (TT), and free flow travel time (TT^*). Equation 5.7 defines the arrival schedule delay variables (i.e. $ASDE$, $ASDL$, and $Delay$), which is consistent with the definition in previous research. PAT denotes the preferred arrival time, AT the actual arrival time, $Delay$ the difference between actual travel time (TT) and free flow travel time (TT^*).

$$ASDE = \max(0, PAT - AT) \quad (5.7)$$

$$ASDL = \max(0, AT - PAT) \quad (5.8)$$

$$Delay = (TT - TT^*)/TT^* \quad (5.9)$$

Various machine learning algorithms [83] are able to derive if-then rules from behavior process survey data. We have tested four proven algorithms including C4.5 [59], PRISM [18], PART [33], and RIPPER [20], and selected PART based on predictive accuracy of the derived search rules on a validation dataset. The complete departure time rule sets are presented below:

Search 60+ min earlier, if

$$[ASDL > 70] \quad \text{Rule 1}$$

Search 30-60 min earlier, if

$$[45 < ASDL \leq 70] \quad \text{Rule 2}$$

Search 0-30 min earlier, if

$$[0 < ASDL \leq 30 \text{ AND } Delay > 0] \quad \text{Rule 3}$$

Search 0-30 min later, if

$$[ASDL > 30 \text{ AND } Delay > 50\%] \quad \text{Rule 4}$$

$$\text{OR } [ASDL \leq 10 \text{ AND } ASDE \leq 40 \text{ AND } Delay \leq 50\% \text{ AND } TT \leq 65] \quad \text{Rule 5}$$

Search 30-60 min later, if

$$[ASDL = 0] \quad \text{Rule 6}$$

Search 60+ min later, if

$$[ASDE > 75] \quad \text{Rule 7}$$

$$\text{OR } [ASDE > 45 \text{ AND } Delay > 10\%] \quad \text{Rule 8}$$

$$\text{Otherwise, search 0-30 min earlier.} \quad \text{Rule 9}$$

Rule 1 states that individuals will consider shifting their departure times earlier by more than 60 if their experienced arrival schedule delay late is over 70 minutes. All other rules can be similarly interpreted. These rules collectively replicate the heuristics individuals use to identify alternative departure times based on their current experiences and knowledge. As spatial knowledge is updated during the search process, the same rule set can generate different alternatives for the same individual.

This set of rules is in a full disjunctive normal form [83], a form of closed-world assumption. In the rule set, each of its variables appears exactly once in every clause. In another word, in each round of searching, any particular searcher can only be classified into one class and follow one of those derived search rules at a time. Therefore, in the set, rules cannot conflict and there is no ambiguity in rule interpretation.

5.2.4 Decision Rules

Once an individual found a new departure time alternative with the search rules in Section 5.2.3, the individual after experimenting with the new departure time will either change or not change departure time. This departure time adjustment decision-making process can be modeled with a set of decision rules. Subjects' actual departure time changing behaviors observed in Part 3 of the survey (see Chapter 3 for details), which allow us to extract decision rules with machine learning algorithms. The empirically derived decision rule set consists of 6 rules, presented below. RIPPER is chosen for its superior predictive performance on vali-

dation dataset, and the clear physical meaning of the derived behavioral rules. The explanatory variables in the decision rules include: preferred arrival time (*PAT*), departure time (*DT*), preferred departure time (*PDT*), travel time (*TIME*), household income (*INCOME*), trip purpose (*PURPOSE*), fuel cost (*FC*), and toll cost (*TC*). The variable *n-peak* is a dummy variable that is equal to one if the trip occurs during off-peak hours, and zero otherwise. Δ denotes changes or percentage changes from attributes of current departure time choice.

The rules are listed as follows. Similar to the search rules, this set of decision rules is also in disjunctive normal form (i.e. if a particular instance decides not to switch, then it must continue to use its habitual departure time).

Switch to the alternative departure time, if

$$[\Delta TIME \leq -35\% \text{ AND } \Delta FC \leq -8\%] \quad \text{Rule 1}$$

$$[\Delta TC \leq \$2.5 \text{ AND } \Delta ASDL \leq -48\%] \quad \text{Rule 2}$$

$$[\Delta TC \leq \$2.4 \text{ AND } INCOME \geq \$150K \text{ AND } \Delta ASDL \leq -31\%] \quad \text{Rule 3}$$

$$[n\text{-peak} = 1 \text{ AND } PURPOSE = Other \text{ AND } \Delta TIME \leq -8\% \text{ AND } \Delta ASDL \leq 53\%] \quad \text{Rule 4}$$

$$[\Delta ASDE \leq -20\% \text{ AND } \Delta TC \leq \$0.7] \quad \text{Rule 5}$$

$$\text{Otherwise, continue to use the current departure time.} \quad \text{Rule 6}$$

There apparently exist perception thresholds in departure time changing behavior. For instance, Rule 1 implies individuals will change departure times as long as travel time and monetary cost can be reduced by 35% and 8% respectively. Variable “toll cost” is represented in several rules, which is evidence of individuals’ responses to dynamic congestion pricing. For instance, the second rule can be inter-

puted as follows: if the toll cost is not too high (less than 2.5 dollars), individuals will use the toll facility in order to avoid being late at work (in this case, reduce the arrival schedule delay late by 48%).

5.2.5 Evaluation

Validating the rule sets is an important process proving the model’s credibility. Usually when the study involves a vast supply of data, the validation can be conducted on a large test dataset while the model is estimated from another dataset called training set. In this research, however, we only have limited data. Thus, at this stage, we conduct within-sample validation, applying ten-fold cross-validation which is typically seen in most practical limited-data situations [43]. Future research may explore how innovative data collection and advanced survey methods, such as web-based interactive games, simulation-based group dynamics, GPS surveys, and smart-phone applications, can support and improve the validation.

In the ten-fold cross-validation, the original data sample is first randomly partitioned into ten sub-groups. One sub-group is retained as the test set. The rest nine sub-groups are used as the training set. Then the estimation and validation process is repeated ten times so that each data sample is used exactly once for validation. This process is carried out for evaluating the search rules and the decision rules. The cross-validation accuracy for the search rules is 61.1%, while six search scopes have been specified in the rules set. And the validation of the decision rules can get 80.5% correctly classified instances. Table 5.1 reports the confusion matrix

for the search rules.

Table 5.1: The Confusion Matrix for the Search Rules

Search:	a	b	c	d	e	f
a: 60+ min. earlier	8	5	2	1	0	0
b: 30-60 min. earlier	5	14	0	2	0	2
c: 0-30 min. earlier	2	0	6	0	1	0
d: 0-30 min. later	0	5	0	6	0	2
e: 30-60 min. later	1	0	2	0	9	0
f: 60+ min. later	0	1	0	4	0	12

5.2.6 Behavioral Departure Time Equilibrium

The quantitative model of departure time choice based on the positive behavior theory proposed in Section 5.1 has been fully developed and validated in Sections 5.2.1 to 5.2.5. According to this model, a behavioral departure time equilibrium (BDTE) will be achieved when all individuals in the transportation system have subjective search gains lower than their respective perceived search costs, and therefore stop searching for alternative departure times. When system conditions change due to increasing level of congestion and/or policies such as dynamic pricing, flexible work hours, and other peak spreading incentives, an existing BDTE will be disturbed and certain individuals will restart the search process and potentially adjust their departure times until the system reaches a new BDTE.

Equations 5.3, 5.4, and 5.5 guarantee the existence of the BDTE, because subjective search gain decrease as number of searches increases. There exists a sufficiently large number, N^* , such that for a particular individual her/his subjective search gain will become lower than her/his perceived search cost which is a con-

stant. The largest N^* across all individuals determines the maximum number of search iterations for the transportation system to arrive at the BDTE, which proves its existence. However, BDTE is not stable in that after an infinitesimally small disturbance, the system is not guaranteed to return to the original BDTE due to historical dependency in the behavioral process represented in the positive departure time choice model. Computational properties of BDTE are explored further in the next section.

5.3 Demonstration

The positive departure time choice model can be combined with various macro-/meso/micro-scopic network traffic models for peak spreading analysis. Such applications require an initial time-sliced origin-destination (OD) matrix and an initial dynamic network user equilibrium. To analyze the impact of a particular policy scenario on peak spreading, an iterative procedure needs to be executed, where simulated network congestion statistics are transferred from the traffic model to the departure time model and updated time-sliced OD matrices from the departure time model to the traffic model. After the joint departure time and traffic equilibrium is obtained, the peak spreading effect of the tested policy scenario is quantified.

In this section, we present a numerical example to demonstrate how the positive departure time choice model developed in the previous section can be applied to estimate peak spreading effects due to increased level of congestion on a linear corridor. The model is also ready to be applied to other policy scenarios with expected

peak spreading effects (e.g., dynamic pricing, flexible work hours) on a general network. The Bureau of Public Roads (BPR) volume-delay function is selected herein to compute traffic congestion for simplicity. In the next Chapter, the positive departure time choice model is integrated with TransModeler (microscopic) traffic model for the before-and-after peak spreading study on a new toll road in Maryland. The numerical example is set up as follows:

- Link capacity is 1,600 vehicles per hour.
- Link length is 33 miles, which is the average commuting distance of all subjects in the survey described in Chapter 3.
- The base-case scenario is characterized by an initial demand in 20-minute intervals from 4 a.m. to 11 a.m., illustrated by the thin dotted line in Figure 5.3.
- The policy scenario assumes a uniform 30% increase in OD demand across all time intervals (see the thick dotted line in Figure 5.3), which is expected to cause significant increase in congestion (especially during the peak hours of the study period) and subsequently adjustment of departure times for certainly commuters. And
- Commuters' arrival times in the base case are assumed to be their preferred arrival times.

The iterative implementation of the positive departure time choice model and the BPR traffic model predicts significant peak spreading effects, and the final OD

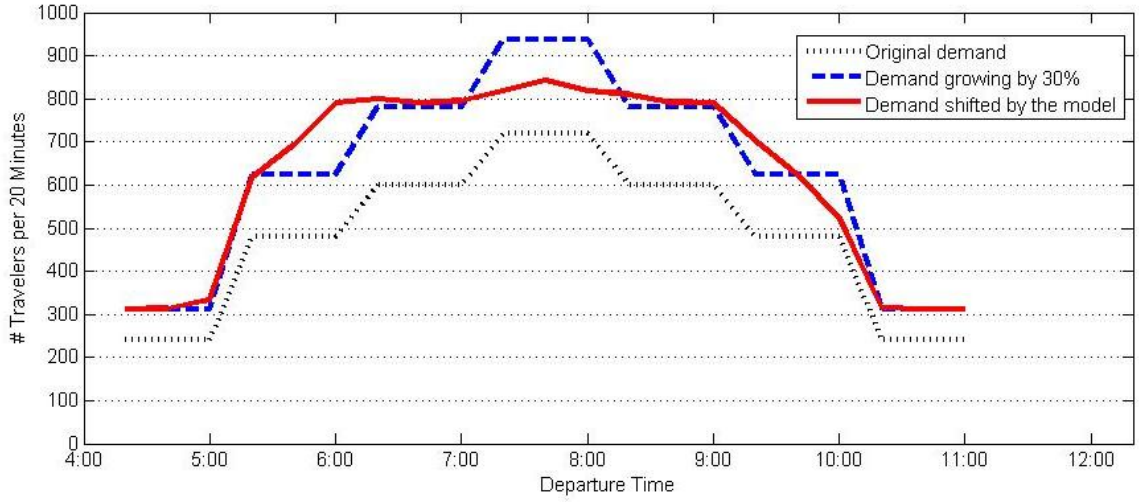


Figure 5.3: Peak Spreading Effect of the Numerical Example

demand at the new equilibrium after departure time adjustments is shown by the solid line in Figure 5.3. About 14% of the commuters who originally depart between 7 a.m. and 8 a.m. now depart either before 7 a.m. or after 8 a.m. (from peak-peak to shoulder peak). About 4 percent of trips between 6 a.m. and 9 a.m. in the base case now occur either before 6 a.m. or after 9 a.m. (from peak to off peak). Consequently, the original 3-hour peak period (6 a.m. to 9 a.m.) has expanded to 4 hours (5:30 a.m. to 9:30 a.m.). The predicted peak spreading pattern appears to be reasonable.

An in-depth examination into the equilibration process predicted by the positive model reveals interesting behavioral adjustment dynamics. Figure 5.4 presents two convergence measures in the positive behavior modeling approach: number of individuals changing departure times (bottom line) and number of individuals searching for new departure times (top line). Results show that the most significant behavioral adjustments occur within the first two weeks, as the number of individu-

als changing departure times decreases quickly. After 50 days, 2% of the commuters are still searching and only 0.24% of the commuters are still changing departure times.

Since the most significant behavior adjustments occur in the first two weeks, we

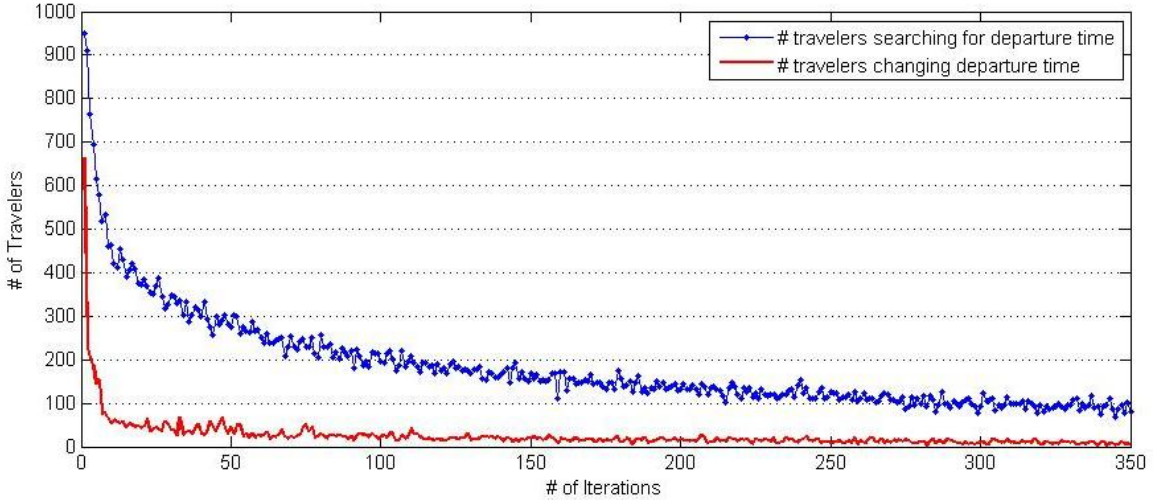


Figure 5.4: Model Convergence

also examine the evolution of congestion in various departure time intervals in Figure 5.5. With 30% demand increase, delay increases from 25 minutes to 70 minutes between 7 a.m. and 8 a.m., which causes long schedule delay late for peak-hour commuters. In the first two days, a large number of these commuters departure about an hour earlier between 6 a.m. and 7 a.m. This actually leads to longer delay between 6 a.m. and 7 a.m. than delay from 7 a.m. to 8 a.m. Commuters continue to adjust their departure times in the next several days, and some of them switch back to 7-8 a.m. departure times and some others depart even earlier (before 6 a.m.). Commuters who originally depart after 8 a.m. only made minor adjustment

because departing earlier results in much longer delay and departure later causes increase in schedule delay late. Nevertheless, we can still observe some departure time shifts from 8 - 9 a.m. to 9 - 9:40 a.m.

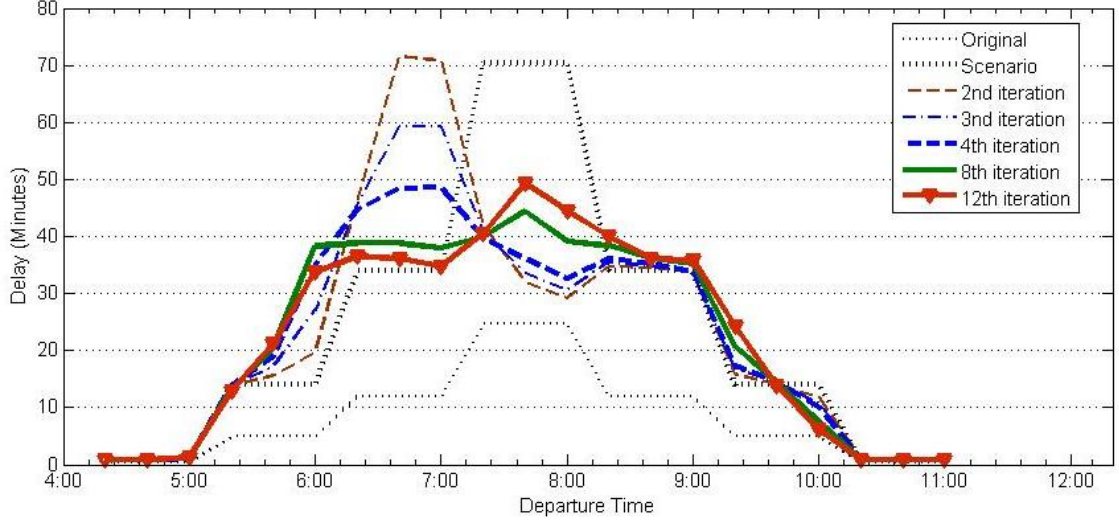


Figure 5.5: Day-to-Day Delay Evolution by Departure Time Intervals

5.4 Summary

This chapter applies a positive behavioral theory to model departure time choices and peak spreading effects. The theoretical framework removes assumptions of perfect information and maximum utility. Instead, travelers' spatial knowledge, learning, subjective beliefs, perception, search for alternatives, and decision-making with limited computational abilities are explicitly theorized and modeled with empirical data. The proposed positive approach enhances both our understanding of the travel decision-making process and the realism of departure time choice models.

The positive departure time choice model is fully operational, and can ready to be integrated with traffic models (e.g. microscopic traffic simulators, dynamic traffic assignment models) or demand models (e.g. activity-based/micro-simulation models) for various transportation operations and planning applications that require peak spreading analysis. The numerical example presented in the chapter highlights the capabilities of the positive model in estimating rich behavioral dynamics, such as day-to-day evolution of congestion by departure time intervals and individual-level learning, search, and decision-making processes over time.

A possible future research direction lies in the application of the positive theoretical framework and modeling methods to multidimensional travel decision-making analysis (i.e. not just departure time choice, but integrated routing, scheduling, mode, destination, and trip frequency decisions).

Chapter 6

Integrating the Departure Time Model with Large-Scale Traffic

Simulation Models: A Case Study

Existing traffic models often neglect departure time change as a possible response to congestion and/or policy changes. Moreover, they often lack a formal scheme modeling how travelers accumulate experience gathered from repetitively traveling through the network and how they make their daily travel decisions based on the accumulated knowledge. This Chapter proposes an integrated modeling framework to address these shortcomings.

Previous chapters focus on the development of a departure time choice model. Different modeling approaches have been discussed and tested. Chapter 5 has developed a positive rule-based model considering learning, adapting, and search behavior. In this chapter, an agent-based micro-simulation approach is applied, wherein travelers base their consecutive departure time decisions on the rule-based model developed in Chapter 5. The agent-based behavioral model is then linked to a microscopic traffic simulation model to incorporate individuals' daily departure time choices into system-level performance and traffic operations analysis. The feasibility of this approach is supported by a case study whose simulation system is based on a real-world network - the Inter-County Connector corridor-level network in Maryland State.

6.1 Overview

Thanks to the computational power that had been greatly enhanced during the past half century, micro-simulating a huge number of vehicles/vehicle platoons in a large-scale network becomes possible. It has been gradually revealed that microscopic/mesosopic traffic simulation models exhibit strong advantages in capturing detailed traffic dynamics and have been approved in practice a valuable tool for evaluating corridor capacity expansion and traffic operation improvements. Their applications have recently been extended to address a broader range of transportation-related issues, including congestion management, multimodal corridor improvements, evacuation planning, land use and economic development. However, a comprehensive analysis of many of these issues requires models that can consider various demand responses to these traffic management strategies such as peak spreading, modal shifts, and traffic diversions at the corridor and regional levels, all of which are conventionally taken as given in simulation models. Another challenge for applying micro-simulation models to large network is due to the difficulty of obtaining reliable travel demand data (usually as time-dependent origin-destination matrices).

6.2 The Agent-Based Micro-Simulation

Therefore, this study develops a micro-simulation framework (see Figure 6.1) to describe the effect of learning and departure time search and integrate agent-based travel behavior models with large-scale microscopic traffic simulation models.

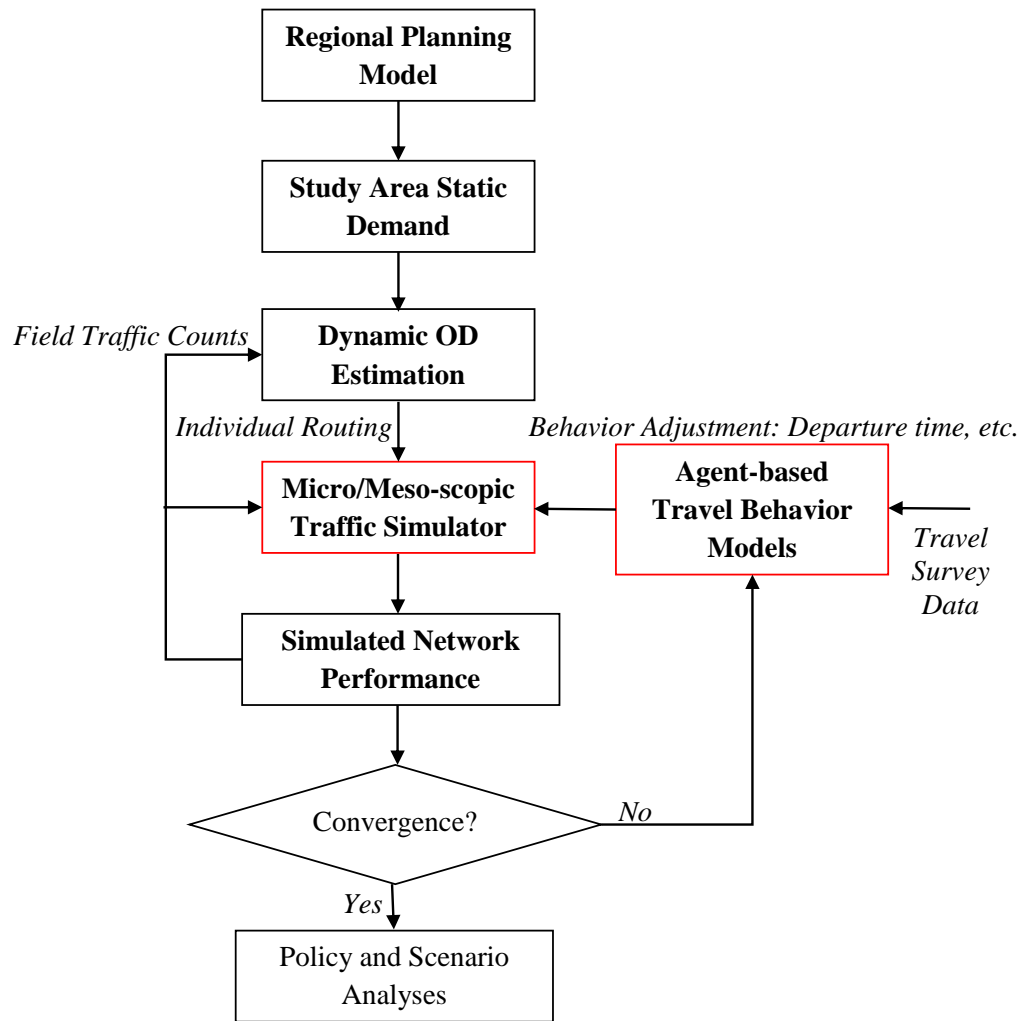


Figure 6.1: Framework of the Integrated Model

The two red boxes highlight the two important components of the agent-based micro-simulation:

- *Agents.* Individuals' learning and knowledge accumulation, departure time searching processes, and decisions are simulated. In other word, agents are hereby modeled individually that they are able to acquire information through experience and use the information to update their perception and search/decision rules. The rule-based behavioral model is documented in Chapter 5.
- *Environment.* The environment where the agents interact is represented by a microscopic traffic simulation model. The traffic model generates output (simulated travel time, experienced delay, etc.) for each trip, which is fed back to the behavioral model to update agents' knowledge and travel decisions.

The framework, as presented in Figure 6.1, is then applied to the case study of the Inter-County Connector (ICC) region in the North Washington D.C. metropolitan area which also involves I-270, I-495, and I-95 corridors. The ICC (see Figure 6.2), recognized as the most significant and high-profile highway project in Maryland since the completion of the existing interstate freeway system, is a new toll facility connecting two busiest travel corridors (i.e. I-270 and I-95) in the region. Framework set up in this study can support future analysis of transportation policy and operation strategies in this area.

A microscopic traffic simulator is built using TransModeler, one of the major commercial packages for micro-simulation. Models are constructed to build the origin-destination (OD) matrices for the simulator based on demand data obtained

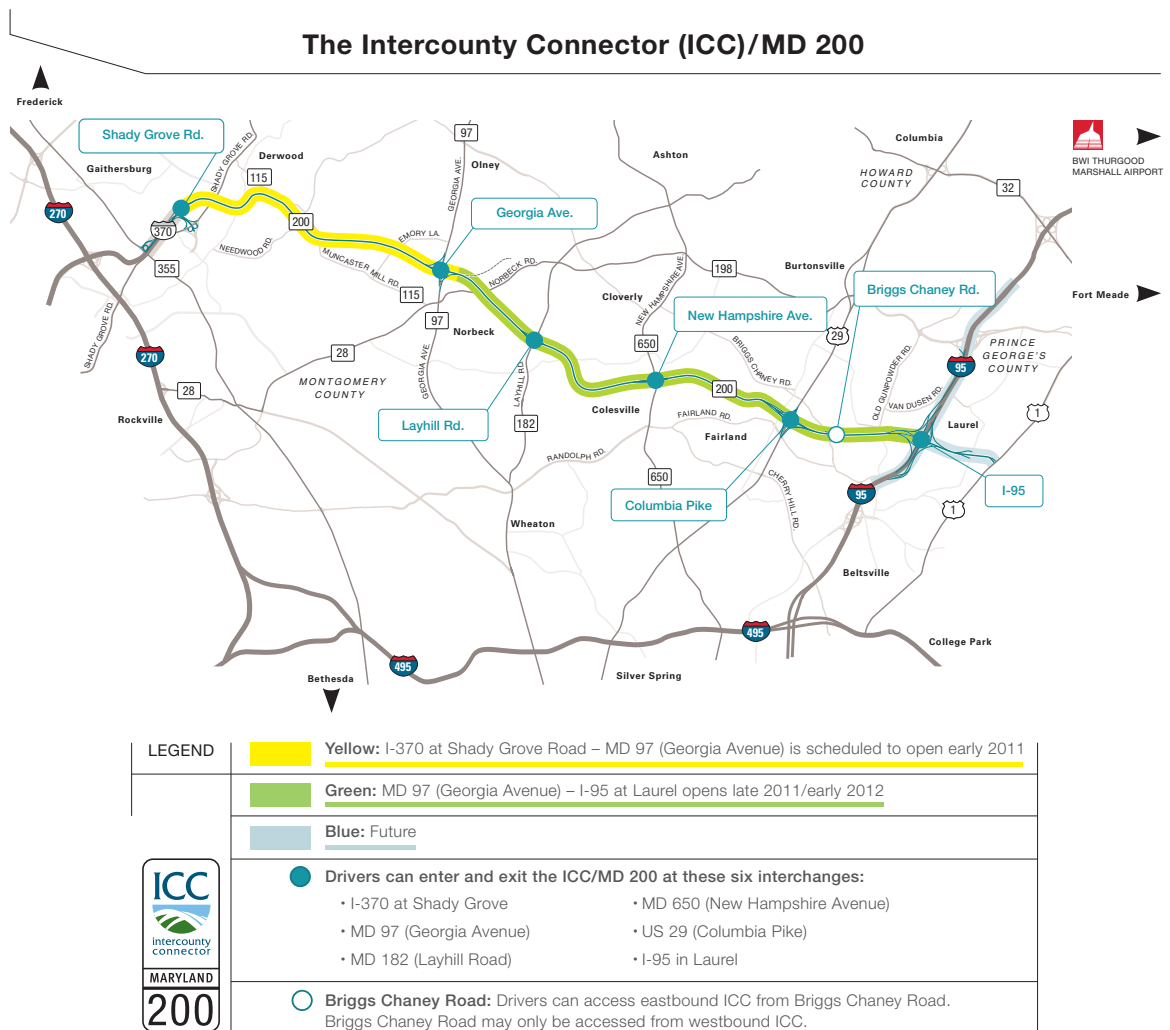


Figure 6.2: The Intercounty Connector Region (Source: Maryland Transportation Authority Website)

from the regional planning model. The dynamic OD matrices and parameters for the micro-simulation model are then calibrated using field traffic counts. On the demand/behavior side, an agent-based departure time choice model is developed as the previous chapters summarize. It is then integrated to capture the behavioral reactions to network changes. The integrated model will operate iteratively until nobody is willing or able to adjust their travel decisions and a stable network condition is thus reached. Details for each component of the model will be discussed in the following sections.

Using agents in the microscopic traffic simulator helps us study the interaction between the individuals and the transport system. The simulator simulates each single trip through a transport network, with a given (fixed) departure time. Microscopic simulators can simulate many details, such as drivers' car following and lane changing behaviors.

Many microscopic traffic simulators (e.g. CORSIM [58], TransModeler [84], VISSIM [35], AIMSUN [6], or non-commercial traffic simulators [19]) have been used in previous studies. These models differ in the underlining car-following models and the way how different traveler/driver modules are implemented. No consensus is reached about the superiority of any simulators in literature. TransModeler is selected in this study because it has a well-developed interface with Geographic Information System (GIS), which is important when working with different data sources.

A microscopic simulation model that includes all freeways, major arterials, most minor arterials, and some local streets along the I-270/I-495/I-95 corridor in

the North Washington D.C. metropolitan area is developed, specifying physical layout of the real-world road network and including signal systems. It covers the central and eastern Montgomery County and the northwestern Prince George's County of the State of Maryland, where several new developments, such as Great Seneca Science Corridor (GSSC) in West Gaithersburg and military bases in Fort Meade, has been proposed. The Inter-County Connector, a new freeway currently under construction, also traverses this area. The simulation network (see Figure 6.3), which includes approximately 7,200 links, 3,600 nodes, and over 40,000 OD pairs, is developed on top of satellite images provided by Google Earth and conforms to the true geometry with high accuracy.

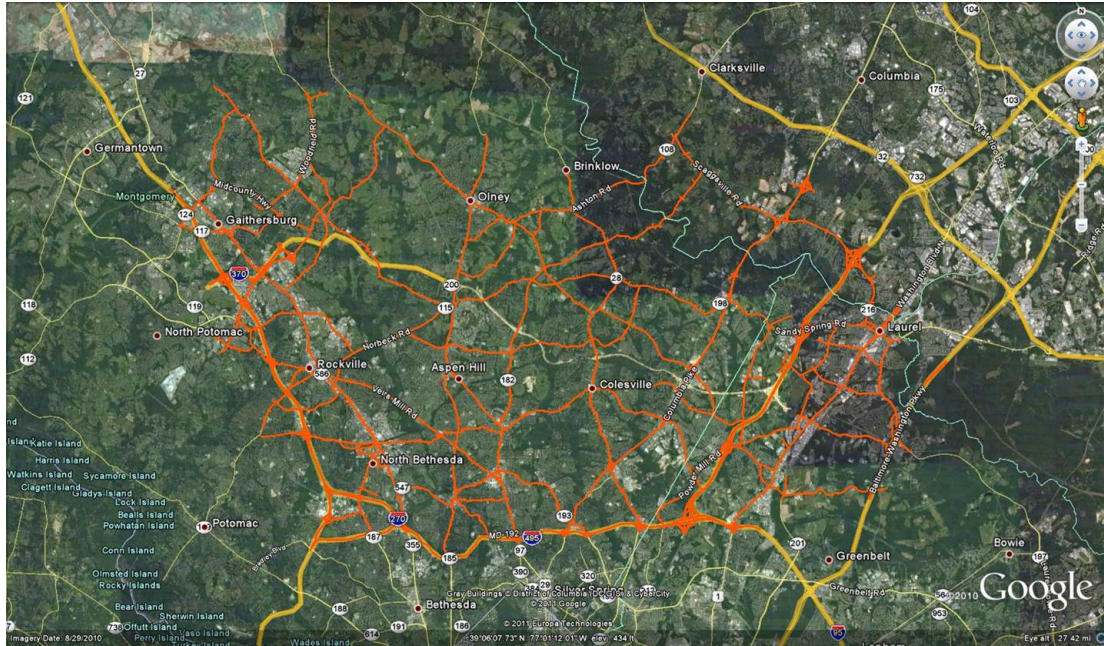


Figure 6.3: Simulated Network (in Red) in the Study Area

It has always been a great challenge to calibrate such a large-scale micro-simulation model. The reasons are three-fold:

- Complete information of traffic control strategies (such as signal timing plans) are usually not available;
- It is extremely hard to obtain the dynamic origin-destination (OD) tables on large network; and
- The number of parameters are so large that it is hard to identify which one (or ones) should be adjusted to match the field counts.

Surprisingly, the first challenge related to traffic control information is not widely discussed in previous studies on large-scale traffic micro-simulation. Ideally, signal timing plan used in the field should also be used in simulation. However, the complete information is usually not available for a large network such as the one in this study. Due to the complexity of various intersection geometry designs in the field, it is almost infeasible to apply the state-of-the-art optimization algorithms in literature, most of which require detailed and extremely accurate inputs about demand patterns and turning movement designs. In this study, the field signal timing plan is applied wherever it is available. A total number of 466 signalized intersections has been implemented, 80 of which use the actual signal plan. For the rest of them, a stylized ring-and-barrier plan (with a cycle length of 150 seconds typically seen from field plans) is applied and the length of green phases is assigned proportionate to the turning demand. Future research will explore more effective approaches to implement optimized signal plans on large network.

Then, this research has done the calibration of the dynamic OD. The algorithm seeks to match the observed link flow by adjusting the OD demand. The

procedure starts from the static OD matrices obtained from the regional planning models. Then, a variation of the Multiple Path Matrix Estimation Method (MPME) proposed by Nielsen [54] is applied to estimate and adjust the dynamic OD. After 10 rounds of iterative calibration, the root mean square error (RMSE) measure falls below 15%. Given the size of the network and the associated computational burden, the research team claims satisfaction with the calibration results and reserves further calibration efforts for future research. More details about this calibration process can be found elsewhere [86].

The third difficulty, the large number of parameters controlling both driving and traveling behavior, has been extensively studied in previous research focusing on the development of microscopic traffic simulation models. Due to the complexity of this problem, this thesis will use the recommended value for most parameters and only make minor changes whenever necessary (for instance, the drivers' value of time distribution).

6.3 Scenario Analysis

This scenario test demonstrates how the aforementioned departure time choice model is integrated with the traffic micro-simulator and how the peak spreading is achieved by the integrated model. Overall, the model is capable to predict individuals' departure time changes responding to various road conditions (e.g. different congestion level, varied toll cost, etc.) for the entire network when considering developments that are planned for the next 10-30 years. This scenario considers the

additional trips generated in the study area due to planned growths in Gaithersburg.

West Gaithersburg is part of the Great Seneca Science Corridor (GSSC) Master Plan; which is proposing the development of 4,360 acres in the center of the I-270 Corridor. This development will be under construction for the next 25-30 years and is to be named the Life Science Center (LSC). The LSC will add 5,750 additional residences and is projected to attract 52,500 jobs (based on existing, approved, and proposed development) (The Maryland-National Capitol Park and Planning Commission). This development will add a substantial amount of automotive volume to the surrounding network. Therefore, for demonstration purpose, in this study we assume that the West Gaithersburg developments will generate 30% more travel demand. The additional demand will change the congestion pattern in the region, and thus motivate some travelers to adjust their departure time accordingly. The updated OD tables will be simulated in TransModeler to generate new traffic pattern, which will in turn be fed back into the agent-based departure time choice model until the dynamic OD adjustment achieves a stable pattern. Other scenario features are listed below:

- The base scenario adopts an original dynamic travel demand (20-minute interval);
- The tested scenario assumes 30% higher travel demand generated from the LSC study area (i.e. Centroid 77, 78, 168, and 169 in Figure 6.4) based on the base case; and
- Peak spreading effect for traffic going through this area is also considered and

tested. As an explorative process, this study only considers the closest external station (Centroid 170) while keeps departure time pattern for demand from other more remote TAZ centroids unchanged. This assumption can be easily relaxed later.

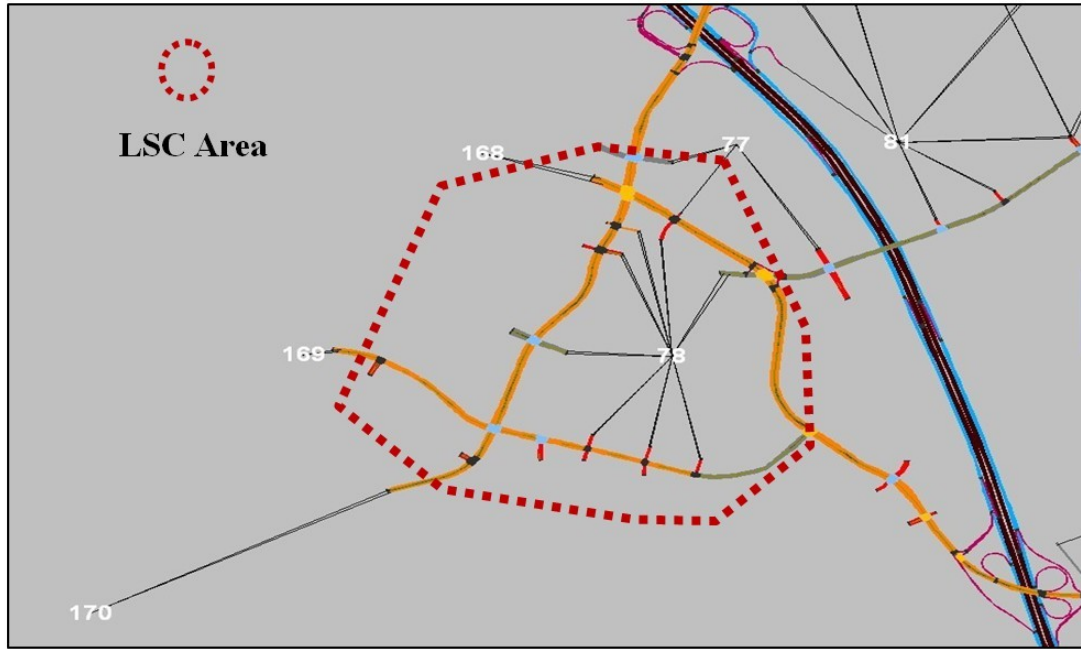


Figure 6.4: The LSC Study Area in the Microscopic Traffic Simulator

As aforementioned, for comparison purposes, the scenario has tested the response of both the demand generated from the LSC study area and the travelers going through this area. Assuming that individuals' preferred arrival time is their individual arrival time in the base case without increasing the demand, travelers who are now experiencing higher schedule delay and longer travel time due to the demand growth are more likely to consider deviating their departure schedules. After 8 iterations, the departure pattern becomes stable and the results are summarized in Figure 6.5 and 6.6.

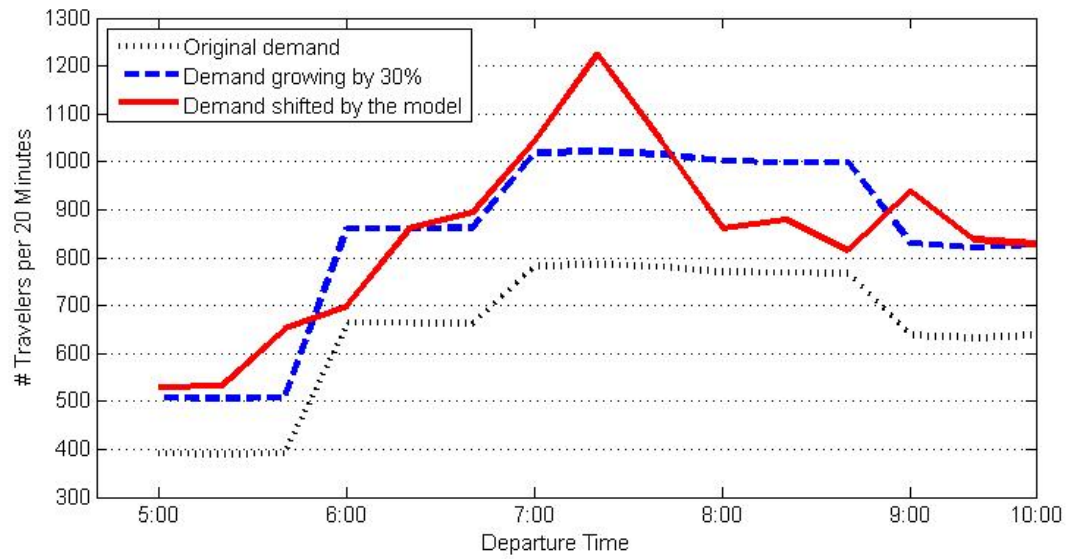


Figure 6.5: Peak Spreading Effect of the LSC Traffic

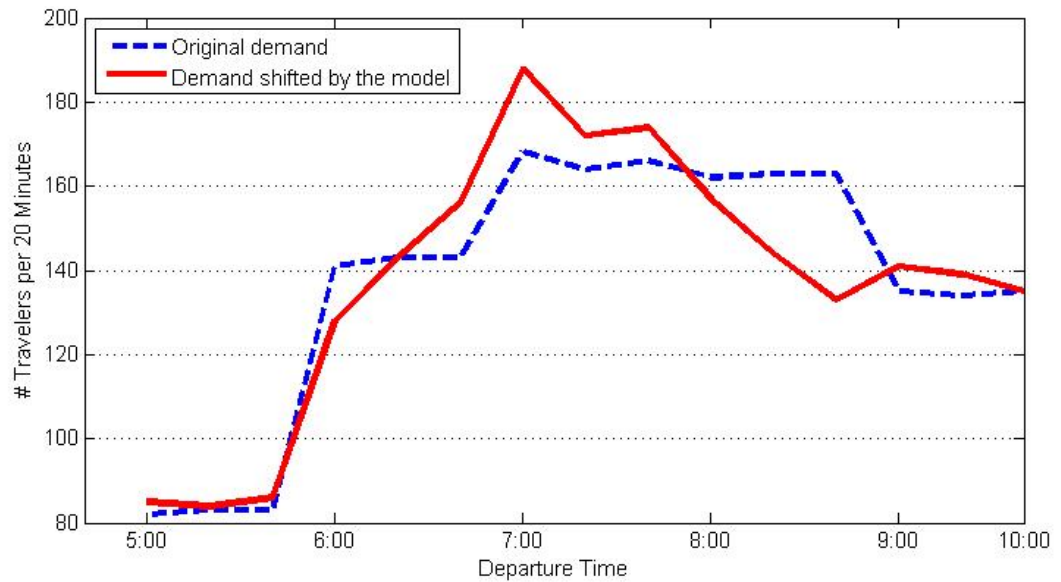


Figure 6.6: Peak Spreading Effect of the Through Traffic

Depicted in Figure 6.5, as the congestion deteriorates, a number of travelers originally traveling between 8 a.m. and 9 a.m. leave earlier to avoid being late. This forms a new peak in the demand pattern. Evidently, travelers from the LSC zones begin to consider shoulder hours (time periods that are slightly earlier or later than the a.m. peak period) as their alternative departure time. Additionally, as the demand grows, the congestion in LSC area is expected to be exaggerated. Thus, the external travelers traversing this region during peak hours are also likely to consider switching departure times to avoid possible delay. As illustrated in Figure 6.5, the model is capable to capture this behavioral change as well. Although the travel demand remains unchanged, the travelers going through the study area also adjust their departure schedule to adapt to the new travel condition in LSC region.

This scenario test demonstrates the capability of the integrated model in representing individuals' behavioral response to various travel conditions. The results overall illustrate a reasonable departure time shift in response to the assumed more congested situation. As displayed in the Figure 6.5 and 6.6, about 6.2 percent of peak-hour trips have switched to depart either earlier or later to avoid higher congestion and delay. Moreover, the original 3-hour peak period (6 a.m. to 9 a.m.), as predicted by the model, has spread out to cover a wider time period (approximately from 5:30 a.m. to 9:30 a.m., Figure 6.5). Figure 6.7 illustrates the evolution of congestion level. As drivers getting reasonably familiar with the time-dependent travel condition, the extreme delay has gradually been mitigated.

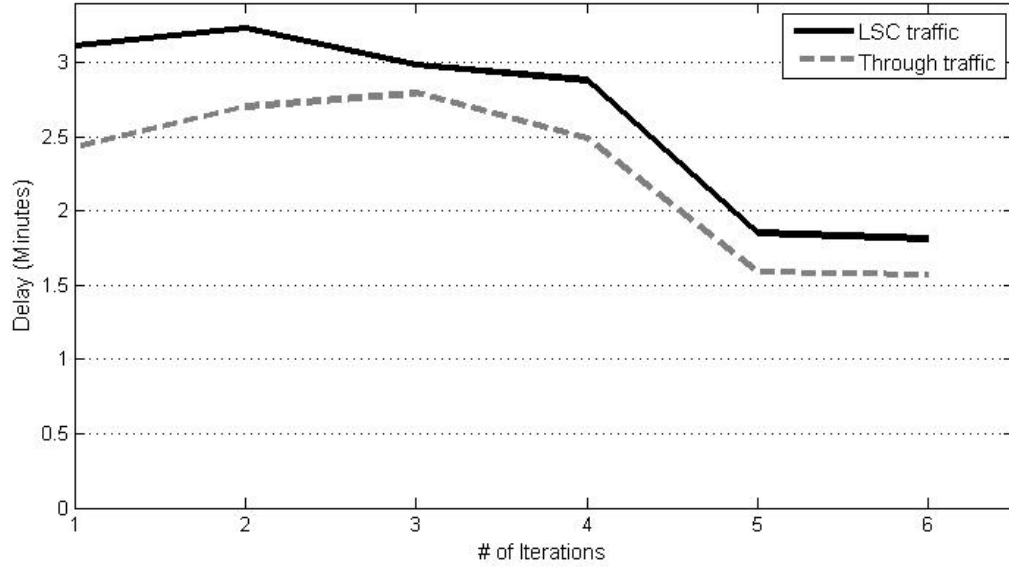


Figure 6.7: Day-to-Day Congestion Evolution

6.4 Summary

This chapter is concerned with the integration of demand models and traffic models. In particular, a positive rule-based departure time choice model has been integrated with a large-scale traffic micro-simulation to capture the behavioral responses to traffic condition changes. We reiterate that the rule-based model differs from the utility-based modeling paradigm which is widely used in previous studies. Moreover, it is intuitive to interpret and its implementation only involves a series of logic evaluation and is more efficient compared to utility evaluation. A multi-corridor microscopic traffic simulation tool has been set up based on the Transmodeler platform. Although many challenges still exist for the calibration of large-scale simulation-based traffic models, the iterative calibration process proposed in this study works reasonably well. Future research is needed to further improve

the calibration accuracy.

Moreover, this positive model of learning and decision-making can be generalized to account for multiple choice dimensions such as mode and destination, departure times, and routes. This agent-based modeling approach provides an easier way to maintain consistency in simultaneous decisions of different choices (the prefer arrival time of individual agent could affect both departure time and mode choice (such as HOV for higher reliability)). In this chapter we only focus on departure time choice and assume that decisions on other dimensions are constrained. The case study well demonstrates its potential in capturing various behavioral reactions to system-level performance changes and policy initiatives. The inclusion of multiple decision dimensions is left for future development.

The integration of agent-based travel behavior models with micro-simulation model also provides a low-cost resource for capturing individual experience and network conditions, and thus makes such models operational in policy analysis. This framework also provides a valuable tool for the evaluation of new transportation infrastructure, such as the ICC corridor currently under construction, and its operation strategies. More research efforts are needed to explore the full potentials of the integrated model.

Chapter 7

Conclusion

This thesis focuses on modeling departure time choice and testing the integration of the behavioral model and the simulation-based traffic models. After reviewing previous research in modeling departure time choice as well as the papers describing the integrated models, the survey design and data collection procedure has been introduced in the Chapter 3. Then, two departure time choice models have been developed in the Chapter 4 and 5 based on different theoretical framework (i.e. utility maximization theory v.s. rule-based positive theory). In the Chapter 6, the rule-based model has been applied in a real-world traffic simulation study built on the ICC network in Maryland State. From the integration work, the merit brought in by the combination of the behavioral models and the traffic models, as well as the usefulness and effectiveness of the rule-based positive approach, has been highlighted.

7.1 Discussions

This thesis aims at making contributions to both the state-of-the-art and the state-of-the-practice of the departure time choice modeling and its applications.

Based on the normative utility maximization theory, a conditional logit model, a mixed logit model, and a latent class model regarding carpooling preference have

been estimated in the Chapter 4. The latent class model is supported by stronger statistical results, interpreting the heterogeneity in another context. Its class probability model suggests that younger drivers and current carpoolers are more likely to belong to the user class whose decision is more sensitive to travel time, toll cost, and fuel cost. Secondly, the model also manifests that there exists a group of drivers having more fixed travel schedule and preferring carpooling rather than paying toll to avoid possible extreme delays. These are interesting findings, invoking further considerations in incentive-based schemes for congestion management.

The discrete choice analysis of departure time scheduling is the main-stream school of research during the past several decades. However, the survey data suggests that travelers are not perfectly rational, given the fact that most of them only search 2 to 6 alternative departure times. In the Chapter 5 of the thesis, a positive modeling framework has been proposed and estimated. This represents a departure from strong rational behavior assumptions for travel modeling and analysis, which is one of the major contributions of this thesis. Nevertheless, it usually implies needs for additional behavior process data. Whether or not the increased data need can be justified by improved model realism and model performance in applications has been a subject for debate. This thesis here employs retrospective recall and joint reveal-/stated preference survey to gather necessary behavior process data, which represents a marginal increase in data collection effort compared to the traditional utility maximization approach. Future research may explore how advanced survey methods such as web-based interactive games, simulation-assisted group dynamics, GPS-surveys, smart-phone applications, and social networking tools can improve

the affordability and quality of behavior process data, and support the positive modeling method.

In the discrete choice models, the work schedule flexibility is considered initially in the model but not statistically significant when included as a dummy variable in the utility function. However, this variable is actually a crucial factor. There are studies considering the circumstances where departure time choice is affected by factors such as work schedule flexibility and other scheduling constraints such as child-care, dropping spouse, and other activities before work [63]. Thus, these variables should be carefully considered in the further research. Moreover, when considering congestion pricing, the toll charge could cause an additional penalty for drivers with inflexible schedule. For this group of people, certain policies, such as before/after-work childcare facilities provided by the employer, could greatly affect their departure time choice and thus should be measured in conjunction with the pricing policies.

With the workable tool deviating drivers' departure time, the Chapter 6 links the rule-based departure time model to a large-scale traffic simulation and micro-simulates behavior changes for each individual, in order to capture the behavioral responses to traffic condition changes. Although many challenges still exist for the calibration of large-scale microscopic traffic simulation model as discussed in the chapter, the intuitive iterative calibration process proposed in this case study works reasonably well. Future research is needed to further improve the calibration accuracy.

7.2 Contributions

The major contributions made by this thesis are listed as follows:

- Exploring the discrete choice models and highlighting the merits of the latent class modeling, which is largely unexploited in travel behavior research.
- Discovering an alternative approach in parallel to the utility-based normative approach. This rule-based model considers the drivers' actual behavior rather than the behavior that maximizes the utility.
- The corresponding survey data collection necessary for the estimation of the rule-based positive model has been designed and conducted with relatively low cost and low respondent burden.
- Demonstrating the usefulness and effectiveness of the integrated modeling framework in the real-world network by performing a case study on the ICC multi-corridor network in Maryland State. It may be noted that such application in the large-scale multi-corridor network is very rare.

7.3 Future Research

A utility-based departure time choice model and a rule-based positive model have been developed. And the effectiveness and practical realism of the integrated model have been demonstrated in the thesis. In the future, certain improvements on this study can be foreseen by the author. They are as follows:

- Firstly, the complex departure time decisions need for better representation.

As a major contribution, individuals' preference towards tolling and HOV/HOT lane is revealed to some extent in the latent class model. Given the richness of the dataset, jointly modeling the lane choice and departure time choice may further enhance the model's ability in this regard as the survey combines multiple dimensions of choices.

- Secondly, without specifying the departure time periods as the alternatives in the survey, the empirical study ends up using discrete choice methodology where the IIA assumption cannot be avoided. We may build more flexible models such as error component logit and generalized nested logit models to relax the strong assumptions on which our current models heavily rely.
- Thirdly, future research may also explore the innovative data collection, including web-based interactive games, simulation-assisted group dynamics, GPS surveys, smart-phone applications, social networking tools, and so forth. These advanced methods may enhance the behavior data sources and support the positive modeling method.
- Another possible direction lies in the extension of the positive theoretical framework and modeling methods to multiple travel decision-making processes, integrating routing, trip scheduling, mode choice, destination choice, and trip frequency decisions.

Appendix A

Departure Time Choice SP Survey Design

Table A.1: Estimation Results for the Conditional Logit Model

Variables	Normal	HOT Lane	HOV Lane
Departure Time	$DT - 40 \text{ min}; DT - 20 \text{ min}; DT; DT + 20 \text{ min}; DT + 40 \text{ min}$		
Total Travel Time Range (min.)	$TT_{\min} + 20 \text{ to } TT_{\min} + 30$	$TT_{\min} + 10 \text{ to } TT_{\min} + 20$	$TT_{\min} + 10 \text{ to } TT_{\min} + 20$
<i>If DT in Peak Hour</i>	$TT_{\min} + 20 \text{ to } TT_{\min} + 40$ $TT_{\min} + 20 \text{ to } TT_{\max}$	$TT_{\min} + 10 \text{ to } TT_{\min} + 25$ $TT_{\min} + 10 \text{ to } TT_{\min} + 30$	$TT_{\min} + 10 \text{ to } TT_{\min} + 25$ $TT_{\min} + 10 \text{ to } TT_{\min} + 30$
<i>If DT not in Peak Hour</i>	$TT_{\min} + 20 \text{ to } TT_{\min} + 45$ $TT_{\min} + 20 \text{ to } TT_{\min} + 35$	$TT_{\min} + 10 \text{ to } TT_{\min} + 25$ $TT_{\min} + 10 \text{ to } TT_{\min} + 20$	$TT_{\min} + 10 \text{ to } TT_{\min} + 25$ $TT_{\min} + 10 \text{ to } TT_{\min} + 20$
	$TT_{\min} + 10 \text{ to } TT_{\min} + 20$	$TT_{\min} + 5 \text{ to } TT_{\min} + 10$	$TT_{\min} + 5 \text{ to } TT_{\min} + 10$
	$TT_{\min} + 10 \text{ to } TT_{\min} + 30$	$TT_{\min} + 5 \text{ to } TT_{\min} + 15$	$TT_{\min} + 5 \text{ to } TT_{\min} + 15$
	$TT_{\min} + 10 \text{ to } TT_{\max} - 10$	$TT_{\min} + 5 \text{ to } TT_{\min} + 20$	$TT_{\min} + 5 \text{ to } TT_{\min} + 20$
	$TT_{\min} + 10 \text{ to } TT_{\max} - 20$	$TT_{\min} + 5 \text{ to } TT_{\min} + 15$	$TT_{\min} + 5 \text{ to } TT_{\min} + 15$
	$TT_{\min} + 10 \text{ to } TT_{\max} - 30$	$TT_{\min} + 5 \text{ to } TT_{\min} + 10$	$TT_{\min} + 5 \text{ to } TT_{\min} + 10$
Fuel Cost (\$)	$1.1 \cdot FC$	FC	FC
<i>If DT in Peak Hour</i>	$1.2 \cdot FC$ $1.3 \cdot FC$	$1.1 \cdot FC$ $1.2 \cdot FC$	$1.1 \cdot FC$ $1.2 \cdot FC$
<i>If DT not in Peak Hour</i>	$1.1 \cdot FC$ $1.15 \cdot FC$ $1.2 \cdot FC$	FC $1.15 \cdot FC$ $1.2 \cdot FC$	FC $1.15 \cdot FC$ $1.2 \cdot FC$
Toll Cost (\$)	0	$\$0.3/\text{mile} \cdot \text{distance}$	0
<i>If DT in Peak Hour</i>		$\$0.35/\text{mile} \cdot \text{distance}$ $\$0.4/\text{mile} \cdot \text{distance}$ $\$0.45/\text{mile} \cdot \text{distance}$ $\$0.5/\text{mile} \cdot \text{distance}$	
<i>If DT not in Peak Hour</i>		$\$0.1/\text{mile} \cdot \text{distance}$ $\$0.15/\text{mile} \cdot \text{distance}$ $\$0.2/\text{mile} \cdot \text{distance}$ $\$0.25/\text{mile} \cdot \text{distance}$ $\$0.3/\text{mile} \cdot \text{distance}$	

Appendix B

Survey Variable List

Table B.1: Most Recent Trip Variables

Variables	Description
<i>trip_purpose</i>	1 =commute, 2 =shopping, 3 =social, 4 =other
<i>travel_time</i>	Travel time (minute)
<i>depart_time</i>	Departure time (total number of minutes starting from midnight)
<i>prefer_depart</i>	Prefered departure time (total number of minutes starting from midnight)
<i>arrival_time</i>	Arrival time (total number of minutes starting from midnight)
<i>prefer_arrival</i>	Prefered arrival time (total number of minutes starting from midnight)
<i>distance</i>	Total mileage for the trip (mile)
<i>fuel_cost</i>	Fuel cost (\$)
<i>park_cost</i>	Park cost (\$)
<i>toll_cost</i>	Toll cost (\$)
<i>enter_location</i>	The exit where the driver enters the Beltway
<i>exit_location</i>	The exit where the driver exits the Beltway
<i>shortest_trip</i>	The shortest experienced travel time for the same travel (min.)
<i>longest_trip</i>	The longest experienced travel time for the same travel (min.)
<i>tt_min_495</i>	The shortest travel time on the Beltway for the same travel (min.)
<i>tt_max_495</i>	The longest travel time on the Beltway for the same travel (min.)

Table B.2: Socio-economic Variables

Variables	Description
<i>gender</i>	1 =commute, 2 =shopping, 3 =social, 4 =other
<i>age</i>	Travel time (minute)
<i>income</i>	Departure time (total number of minutes starting from midnight)
<i>education</i>	Total mileage for the trip (mile)
<i>occupation</i>	Fuel cost (\$)
<i>workers_per_hh</i>	Number of workers in the household
<i>cars_per_hh</i>	Number of vehicles in the household
<i>vehicle_size</i>	1 =small, 2 =medium, 3 =large
<i>vehicle_age</i>	1 =< 1 year, 2 = 1 – 5 years, 3 = 5 – 10 years, 4 => 10years
<i>work_zip</i>	The ZIP code of the work location
<i>work_start</i>	Work start time (total number of minutes starting from midnight)
<i>flex_avail</i>	1 =work schedule is flexible, 2 =otherwise

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